Algorithmic approaches to simulating animal movement using agent-based models

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Contents

Abstract

New methods for making sense of movement data continue to emerge in response to unprecedented volume of geographic information on moving objects. Geo-computational techniques, including spatial agent-based models, are presented with new opportunities for innovation as people, animals, vehicles, and countless other *objects* are tracked across space and time at an ever-expanding scale and resolution.

This thesis explores algorithmic approaches to agent-based modelling animal movement. Algorithmic approaches to informing, calibrating, and/or validating agent-based models of spatial systems are an open area of research in geographic information science. Following an introduction to animal movement and the objectives of this thesis (chapter one) and a comprehensive literature review of geosimulation approaches to modelling mobility, movement, and migration (chapter two), chapter three demonstrates an innovative geospatial artificial intelligence technique for agent-based simulation of olive baboon (*Papio anubis*) troop movement in Mpala, Kenya. This individual, bottom-up animal movement simulation uses classification trees to develop local movement rationales for baboon-agents. Simulated trajectories depict real-world troop movement corridors across the region. Unexpected emergent behaviour arises in the simulation as animal-agents cross a known, although unprogrammed, river-crossing site. Extensive discussion of this baboon-agent model, along with implications for modelling tightly-coupled socioecological systems follows chapter three.

This contribution to geosimulation and computational movement analysis is published in Transactions in GIS and was presented at an IEEE workshop on geospatial visualisation and the ESRI user conference. The method offers an innovative way of making sense of animal movement data and simulating high-fidelity trajectories using inductive learning artificial intelligence technologies.

Abrege

De nouvelles méthodes pour donner un sens aux données de mouvement continuent d'émerger en réponse au volume sans précédent d'informations géographiques sur les objets en mouvement. Les techniques géoinformatiques, y compris les modèles spatiaux basés sur des agents, offrent de nouvelles possibilités d'innovation car les personnes, les animaux, les véhicules et d'innombrables autres *objets* sont suivis dans l'espace et dans le temps à une échelle et à une résolution toujours plus grandes.

Cette thèse explore les approches algorithmiques de la modélisation des mouvements d'animaux à base d'agents. Les approches algorithmiques visant à informer, calibrer et/ou valider les modèles de systèmes spatiaux basés sur des agents constituent un domaine de recherche ouvert dans les sciences de l'information géographique. Après une introduction sur les mouvements d'animaux et les objectifs de cette thèse (chapitre 1) et une revue complète de la littérature sur les approches de géosimulation pour modéliser la mobilité, les mouvements et la migration (chapitre 2), le chapitre 3 démontre une technique innovante d'intelligence artificielle géospatiale pour la simulation à base d'agents des mouvements de troupes de babouins olivâtres (*Papio anubis*) à Mpala, au Kenya. Cette simulation individuelle et ascendante des mouvements d'animaux utilise des arbres de classification pour développer des logiques de mouvement local pour les agents babouins. Les trajectoires simulées décrivent avec précision les couloirs de déplacement des troupes dans le monde réel à travers la région. Un comportement émergent inattendu apparaît dans la simulation lorsque les agents-animaux traversent un site de franchissement de rivière connu, bien que non programmé. Le chapitre 3 présente une analyse détaillée de ce modèle babouin-agent, ainsi que ses implications pour la modélisation de systèmes socio-écologiques étroitement couplés.

Cette contribution à la géosimulation et à l'analyse computationnelle des mouvements est publiée dans Transactions in GIS et a été présentée lors d'un atelier de l'IEEE sur la visualisation géospatiale et de la conférence des utilisateurs de l'ESRI. La méthode offre un moyen innovant de donner un sens aux données sur les mouvements des animaux et de simuler des trajectoires de haute fidélité à l'aide de technologies d'intelligence artificielle d'apprentissage inductif.

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ABMs Agent-Based Model(s). 32, 59

BRTs Boosted Regression Trees. 56

BULC Bayesian Updating of Land Cover. 25

DRCW First-Difference Random Correlated Walks. 23

GeoAI Geo-spatial Artificial Intelligence. 11, 15

GIS Geographic Information Systems. 11, 14, 22

GIScience Geographic Information Science. 11, 14

GLONASS GLObalnaya NAvigatsionnaya Sputnikovaya Sistema. 12

GNSS Global Navigation Satellite System. 12

GPS Global Positioning System. 12

HMMs Hidden Markov Models. 23

MTUP Modifiable Temporal Unit Problem. 22

NavIC Navigation using Indian Constellation. 12

PGIS Participatory Geographic Information Systems. 27, 59

QZSS Quasi-Zenith Satellite System. 12

RSF Resource Selection Function(s). 23

sABMs Spatial Agent-Based Models. 14

SLEUTH Slope, Land Use, Exclusion, Urban, Transportation, Hillshade. 19, 20

SSF Step Selection Function(s). 23

SVM Support Vector Machines. 20

UTM Universal Transverse Mercator. 34

1 Introduction

Spatiotemporal phenomena often include movement through geographic space and time. While all phenomena can be characterised as occurring in some *phase*[1] space, spatiotemporal phenomena are definitively comprised of a change process with explicit, sometimes uncertain, spatial and temporal attributes (Carnap, 1995; Gudmundsson et al., 2008, 2012; Shekhar, Jiang, et al., 2015). Movement through complex phase space is routinely observed across systems and scales. Whether it be displacement and human migration; cyclists' preferred commuting paths through bustling city centres; or transnational flows of state administered policy, movement through geographic space-time is an important analytic for geographers and geographic information scientists (Laube, 2014; Li et al., 2020; Young, 2002).

In this thesis, I present animal movement as complex spatiotemporal phenomena using Geographic Information Science (GIScience) and complexity theory; demonstrate a novel Geo-spatial Artificial Intelligence (GeoAI) technique for modelling animal movement; and highlight critical considerations for geographers modelling animal movement in tightly-coupled socioecological systems. This work serves to emphasize common ground between geosimulation and computational movement analysis (Crooks et al., 2008; Hadjieleftheriou et al., 2002). Formatted in the order I explored my topic, this thesis introduces animal movement as an ecological problem amenable to Geographic Information Systems (GIS) for managing location data and conducting geospatial analyses, then continues on to include both model and model-making aspects of simulating of animal movement.

1.1 Animal Movement, a Complex Spatiotemporal Phenomena

Aristotle's search for common process(es) underlying animal self-motion across species, system, and scale; connecting the motion of all things, outlined in *De Motu Anamalium*, remains unresolved and a growing area of research for biologists, ecologists, anthropologists, and geographers.

"***Now we must consider in general the common reason for moving with any movement whatever.***" (Aristotle, in *De Motu Anamalium*, 384 – 322 before common era) (Farquharson, 1912)

[1] complex n-dimensional space

In line with the spirit of this statement, technologies designed to track or otherwise monitor animals in geographic space and time have undergone substantial improvements in accessibility and implementation. For example, Global Navigation Satellite System (GNSS) (i.e.,Global Positioning System (GPS), GLObalnaya NAvigatsionnaya Sputnikovaya Sistema (GLONASS), Quasi-Zenith Satellite System (QZSS), Galileo, BeiDou, or Navigation using Indian Constellation (NavIC)), radio-telemetry, or Doppler-based Argos tags can be affixed to an individual to record location over time. Owing to the expansion of tracking technologies, along with laudable initiatives enabling open and free-to-use data-sharing platforms (e.g., movebank, Dryad), an unprecedented volume of valuable tracking data exist across biological taxa[2] and geographic region (Dodge et al., 2008; Kays et al., 2022; Kranstauber et al., 2011; Wilmers et al., 2015). Similarly, innovations in applied remote sensing, bio-logging, and geocomputation have led to better resolved environments (Dodge et al., 2013), and more effective conservation policy (Katzner & Arlettaz, 2020). As traditional methodologies are unable to keep-up, novel methods amenable to analyzing geospatial big (tracking) data are required to take advantage of a growing and increasingly complex ecological and geographic data (Demšar et al., 2015)).

Movement as an emergent complex spatiotemporal phenomena is best demonstrated by mobile and social animal groups. Sumpter et al. (2008) notes that in such cohesive moving animal groups, individual-level interactions between animals lead to movement patterns which are easy to observe, but complex and difficult to characterize. For example, starling (*Sturnidae sp.*) murmurations involve flocks of individuals which appear to turn in unison despite no individual leader, set of leaders, or collective intelligence amongst starlings. Similarly, schools of fish – sometimes existing as massive moving shapes in our seas – avoid predators by morphing into unexpected vacuous shapes seemingly at once. In early work on collective animal movement, Radakov (1973) would frighten small portions of a school of silverside fish (*Atheriniformes sp.*). Radakov observed "wave[s] of agitation" spread across the school faster than displacement of any individual. This provided verifiable evidence of directional information transfer, presumably as a key mechanism for maintaining spatial cohesion in moving animal groups (Sumpter et al., 2008). More recently, analysis focused on directional information transfer in moving animal groups has helped overturn prevailing primatological theory on group navigation (King & Sueur, 2011; Strandburg-Peshkin et al., 2015), establishing new lines of inquiry into collective behaviour from insects to whales (Hughey et al.,

[2]groups of biological organisms at any rank – species, order, family, kingdom etc.

2018).

Interactions, like directional information transfer, come together in unexpected ways sometimes resulting in unpredictable and *emergent* complex phenomena – as is the case for spatiotemporal patterns of animal movement (Giuggioli et al., 2011; King & Sueur, 2011; Nathan et al., 2008; Sumpter et al., 2008). Identifying which components, including when, where, and what interaction a component engages in, is a challenging task traditionally requiring extensive in-field and direct-observation of an animal species population, group, or individual. Although this inquiry is firmly within the domain of wildlife biology, animal ecology, or primatology (Hebblewhite & Haydon, 2010), how components and interactions are represented in-silico[3] is particularly important to geographic information scientists interested in modelling movement as complex spatiotemporal phenomena.

In an effort to unify how animal movement is conceptualised across species and systems, Nathan et al. (2008) theorized four key components underlying all organismal movement: the internal state of an individual, its motion capacity, its navigation capacity, and external factors (Holyoak et al., 2008). This unifying conceptualisation, often referred to as the movement ecology paradigm or framework, is well-adopted by ecologists, has cemented the role of movement ecology in social animal conservation (Chapman & Reyna-Hurtado, 2019) and is well-suited for object-oriented[4] (Grimm et al., 2020) simulation wherein an individual, group, or population is represented as a moving object in digital environmental space.

1.2 Informing Agent-Based Models of Animal Movement

Modelling individual movement using object-oriented data structures enables explicit considerations for both spatial heterogeneity in environment and individual heterogeneity in behaviour, while also aligning with the movement ecology paradigm (Nathan et al., 2008). Spatial heterogeneity of resource distribution; spatial dependence of geographic phenomena; and spatial auto-correlation in data all suggest similar ongoing non-linear effects operating within spatial systems (Florax & De Graaff, 2004). To adequately represent and simulate outcomes resulting from interactions between and amongst objects of such a system, accommodations for both spatial and individual heterogeneity are required (Ahearn et al., 2001; Tang & Bennett, 2010). That is, methods need to be able to consider individual level differences in animal behavioural state, its motion capacity, and navigation

[3]scientific experimentation based on computation

[4]OOD envisions programmatic solutions to be based on classes emphasizing object interaction and characteristics

capacity, as well as spatial variation in external factors as they are expressed at each location.

As popular object-oriented simulation methods, agent-based modeling frameworks equipped with extensions for managing GIS data formats are ideal for modelling movement as an emergent spatiotemporal phenomena (Bonnell, Ghai, et al., 2016; Tang & Bennett, 2010). Agents in object-based, bottom-up simulations possess *states*, *characteristics* or *attributes*, and *methods* or *functions* to enable interaction with one another and the simulated environmental space. Spatial Agent-Based Models (sABMs) (S. Manson et al., 2020) are particularly popular methods for modelling animal movement (Torrens, 2010). Often when agent-based approaches are implemented, expert knowledge (usually acquired from wildlife biologists) is used to inform animal-agent behaviour. Agent-based rules for navigating geographic space are usually derived from either (a) expert knowledge or direct observations encoded as movement rationals; (b) a variant of Djisktra's shortest path algorithms (e.g., A*) to direct animal-agents between origins and destinations; or (c) using behavioural models (e.g., isovist[5] view sheds of the environment) (Chun et al., 2019; Rybarczyk, 2010).

Algorithmic methods offer unique advantages when extracting rationales from environmental and trajectory data (Elith et al., 2006). Algorithmic methods assume data in natural systems are produced in an unknown way, often described as having no prior assumptions about the underlying data model (Bickel et al., 2006; Breiman, 2001). Algorithmic approaches to agent-based modelling offer considerable upside to critical forms of GIScience as they enable methods without strict prioritization of data authority (Sengupta & Sieber, 2007; Sieber & Haklay, 2015). As relationships between inputs are emphasized by whichever dominant patterns are recognized in training data (Breiman, 2001; Elith et al., 2008; Hastie et al., 2009), algorithmic approaches provide a strong contrast to expert-informed models. Such approaches also enable gestalt approaches to simulation, wherein simulated objects, environments, and interaction can be independently modelled and incorporated into a simulation. Algorithmic approaches to informing, calibrating and validating agent-based models are underappreciated despite advances enabling interesting applications.

1.3 Objective

Framed by GIScience, complexity theory, and computational movement analysis, this thesis demonstrates how classification trees may be used to develop rules for agent movement for the purpose of replicating real-world observed trajectories and established movement pathways. The core objec-

[5]geometric volume of space visible from a given point in space

tive of this thesis is make use of large amounts of trajectory data at high spatiotemporal scale to develop a GeoAI approach to bottom-up simulation of animal movement through geographic space. This objective is pursued by using the following research questions to guide my work:

Can agent rules extracted from classification trees be incorporated into an agent-based simulation of an animal group? Do simulated trajectories represent their real-world counterparts? Do animal-agent and real-world animals appear to have similar space use patterns?

This contribution is published in Transactions in GIS (https://doi.org/10.1111/tgis.12770); presented at the IEEE workshop on information visualisation of geospatial networks, flows, and movement; and presented at an ESRI user conference. Following discussion of this classification tree based agent-based movement model, important considerations are provided for simulating tightly-coupled socioecological systems. These considerations were presented at the most recent GIScience workshop on Disruptive Movement Analysis, prompting considerable discussion of disruptive applications of computational movement analysis.

2 Literature Review

This thesis contributes a novel algorithmic approach for calibrating agent-based models of animal movement. To contextualise this work, a comprehensive review of geosimulation and computational movement analysis follows. The review of computational movement analysis cuts across two domains: human mobility and animal movement ecology. Inspired by Laube's topology for a new geographic information object (Laube, 2014), this section is organized into three elements: movement traces, spaces, and places.

2.1 Geosimulation

As geospatial data increases in amounts of available data (i.e., volume), better resolved data (i.e., veracity), and tools for processing, analysing, and presenting data in near real-time (i.e., velocity), geosimulation is brimming with potential for computational movement analysis. At the most recent GIScience session on Geosimulation, Heppenstall et al. (2023) introduced *ExAMPLER*, an exa-scale agent-based model for real-time policy evaluation. Heppenstall et al. (2023) envision a tool which ingests, processes, and provides real-time analysis of how information flows in a simulated system. While ambitious, such a tool would be coveted by policy-planners, and could usher in a new age for simulation. Although software and hardware required for an exa-scale agent-based model remain elusive, spatial data and data management architectures required for peta-scale[6] simulation, analysis, or information visualisation are well-established (Fiore et al., 2018).

Geosimulations are not necessarily computational. For example, the Mississippi Basin Model simulated water-flow for "an area of 1.25 million acres: rivers, tributaries, levees, dikes, flood-walls, and control reservoirs" using 200 acres, folded screen wire, and brushed concrete (Grim et al., 2013; Robinson, 1992). Similarly, the San Francisco Bay model (Huggins & Schultz, 1967) is a physical hydrological simulation to link environmental outcomes with policy intervention. Although no coherent definition of simulation exists, simulations are intended to be isomorphisms of real-world systems in silico, often for the purpose of evaluating policy. It should be noted that computational and physical simulation are fundamentally different as computers do not manipulate real-world objects, as is done in physical simulation (Barberousse & Ludwig, 2008).

Despite recent advances and widespread application across social and natural sciences, consid-

[6]binary prefixes used to describe quantities of data: kilo, mega, giga, tera, peta, exa, etc.

erable disagreement exists across science and philosophy of science on what constitutes computer simulation, what epistemological potential it holds, and whether or not simulation science can contribute to knowledge discovery (Hartmann, 1996; Humphreys, 2009). Simulation, broadly interpreted, has led to ground-breaking discovery in a variety of fields. For example Unruh theorised and later experimented with simulated 'dumb' black holes using sound waves, as opposed to gravitational waves, and has today become foundational to an entirely new approach to black holes physics research (Dardashti et al., 2017; Unruh, 1981, 2016).

2.1.1 Movement, Mobility, and Migration

Two bottom-up simulation technologies in particular, agent-based models and cellular automata models, have extended this potential for in-silico experimentation of spatial systems, contributing to more comprehensive understanding of spatiotemporal phenomena. Torrens (2010) summarize the application of agent-based models for spatial sciences, while O'Sullivan et al. (2016) review agent-based models for land systems dynamics, and Tang and Bennett (2010) review agent-based models of animal movement. Each of these reviews clarify how agent-based models employ simulated space as a medium of interaction (Crooks et al., 2008). This simulated space can be geographically explicit, making spatial ABMs well-suited to visually represent and simulate outcomes related to animal movement in complex adaptive systems (Bonnell, Chapman, et al., 2016; Cenek & Franklin, 2017; J. Liu et al., 2007; Perez et al., 2018).

Modelling spatial decision-making in humans (Hölscher et al., 2013; Mohibullah & Julie, 2013; Orellana et al., 2012; Torrens, 2012) and animals (Ahearn et al., 2001; J. H. Anderson et al., 2017; Bishop & Gimblett, 2000; Tang & Bennett, 2010) has consistently been spurred by development of agent-based models of spatial systems. For example, pedestrian movement through cities is an active and productive area of GIScience and simulation research (Batty, 2001; Crooks et al., 2015; Dijkstra et al., 2001; Haklay et al., 2001; Nasir et al., 2014; Torrens, 2012; Zou et al., 2012).

Simulations perform well in developing models of egress and evacuation in response to disasters in buildings and regions (Y. Huang et al., 2023). Such tools are valuable for policy evaluation given the extent to which individual action (e.g., panic), can aggregate to dire safety concerns (Bernardini et al., 2014; Lin et al., 2010; Mordvintsev et al., 2014; Tan et al., 2015; Wagner & Agrawal, 2014; Zheng et al., 2009). Mixing pedestrian and migration models, researchers have explored crowd dynamics in hurricanes (Chen, 2008; Chen et al., 2006; Kar & Hodgson, 2008; W.

Liang et al., 2015; Reilly et al., 2017; Widener et al., 2015; Widener et al., 2012; W. Yin et al., 2014), earthquakes (Crooks & Wise, 2013; Lichter et al., 2015; Torrens, 2014), fires (Adam & Gaudou, 2017; Ren et al., 2009; Wagner & Agrawal, 2014), tsunamis (Kim et al., 2022; Takabatake et al., 2017; Wang et al., 2016), and bioterrorism (Song et al., 2013). Kim et al. (2022) simulate disaster response across multi-modal networks involving walking, cycling, and driving. In a similar vein, calls to further develop data driven systems approaches to modelling resilience in urban systems have become increasingly pressing with more frequent environmental disaster events (Altizer et al., 2007; Yabe et al., 2022).

Forced human migration, resulting from armed conflict (Estrada et al., 2017; Perez et al., 2018; Suleimenova et al., 2017), are new grounds for simulating movement and resource-allocation inquiry. Global climate change and rapid environmental change have encouraged a number of disaster and emergency related spatial agent-based models (Entwisle et al., 2016; Hassani-Mahmooei & Parris, 2012; Kniveton et al., 2011; Smith, 2014). Simulations of landslides (Avolio et al., 2010, 2017; Lai et al., 2013) as well as fire spread risk (Gaudreau et al., 2016; Russo et al., 2014) using cellular automata complement disaster related movement models.

Similarly, there is an extensive history of developing agent-based models of animal group dynamics, collective behaviour, animal movement ecology, and verifying biological anthropological theory (Bennett & Tang, 2006; Bernardes et al., 2011; Bonnell, Chapman, et al., 2016; Bryson et al., 2007; Grosman et al., 2009; McLane et al., 2017; Musiani et al., 2010; Perez & Dragicevic, 2012; Pirotta et al., 2014). More recently, agent-based models of movement have been developed with the intent of considering contextual information in new ways, and providing alternative simulation methods for trajectory data (J. H. Anderson et al., 2017; Diaz et al., 2021).

Interesting recent examples of agent-based animal movement models include: an African elephant (*Loxodonta africanus*) spatially explicit agent-based model which showcased that simulating high-fidelity trajectories is possible using "a resource-driven model with relatively simple decision rules..." (Diaz et al., 2021); time-geographic agent-based models of animal movement (Loraamm, 2020); and a Muscovy duck agent-based model, developed to offer an alternative simulation technique to correlated random walks (J. H. Anderson et al., 2017). Further algorithmic approaches to agent-based models of animal movement include context-sensitive random walks that incorporate local external factors to simulate movement of two female tigers at forest edges in Nepali communities (Ahearn et al., 2001); genetic algorithms to simulate representative relative-turn angles and step-distance of homing pigeons (*Columba livia domestica*) (Oloo & Wallentin, 2017); reinforcement learning to contextualize risk and reward of agent behaviour (Bennett & Tang, 2006; Sutton & Barto, 1999) and artificial neural networks to assign weights to link environmental features to an agent's internal, spatially-explicit map of its surroundings (Sutton & Barto, 1999).

Finally, a variety of free and open source agent-based modelling frameworks exist to simulate complex spatiotemporal phenomena (e.g., MESA for python based object-oriented simulation with GIS support) (Masad & Kazil, 2015). Many focus on movement, such as MATSIM, and are in use at transportation authorities (Balmer et al., 2009). Recent agent-based models of transportation geography have focused on delivering more sustainable transportation alternatives (Galland, Ansar-Ul-Haque Yasar, et al., 2014; Galland, Knapen, et al., 2014; Hussain et al., 2015; Hussain et al., 2016). As a result, simulations continue to play an active role in shaping urban policy. For example, these models work to identify the optimal allocation, reallocation, and sharing of micro-mobility vehicles (Diallo et al., 2023).

2.1.2 Urban Segregation

Urban and suburban segregation, or self-organization, is often modelled using agent-based models, wherein agents move to locations with individual-specific desired attributes (Ardestani et al., 2018; Crooks, 2010; Guo et al., 2019; Q. Huang et al., 2014; Koch, 2014; Spielman & Harrison, 2014; L. Yin, 2009). Understanding the drivers and spatial dynamics of current gentrification patterns (C. Liu & O'Sullivan, 2016; Nara & Torrens, 2005; Torrens & Nara, 2007) is at the core of a set of current simulation modeling efforts (Jackson et al., 2008; Sabri et al., 2012; Sabri & Yaakup, 2008; Zou et al., 2012), combining cellular automata and agent-based approaches to longstanding geographic questions. Similarly, there is an interest in developing simulations for policy evaluation related to slum formation, expansion, and future establishment (Crooks et al., 2014; Diuana et al., 2006; Diuana, de Farias, et al., 2007; Patel et al., 2012; Roy et al., 2014).

Further, concepts for model calibration, validation and testing borrow from established techniques from urban systems science (Clarke-Lauer & Clarke, 2011; Hui-Hui et al., 2012; Y. Liang & Liu, 2014; Mahiny & Clarke, 2012; Mathioulakis & Photis, 2017; Onsted & Clarke, 2011; Rienow & Goetzke, 2015; Rienow & Stenger, 2014; Wu et al., 2010). For example, Chaudhuri and Clarke (2014), Hua et al. (2014), Nigussie and Altunkaynak (2017), and Jantz et al. (2010) use a well established cellular automata urban growth model – Slope, Land Use, Exclusion, Urban, Transportation, Hillshade (SLEUTH) – to calibrate simulations of urbanization. Similarly, Onsted and Clarke (2011) develop a new method for informing SLEUTH with changing enrollments in a tax concession program for farmers, while Rienow and Goetzke (2015) improve urban growth models using Support Vector Machines (SVM).

2.1.3 Public Health

Spatially explicit epidemiological models started gaining popularity among geographers at the turn of the century (for a detailed review see (Bian, 2013)). Enabled by individual and spatial heterogeneity, agent-based models of disease spread have been increasingly popular for geographers, epidemiologists, and disease ecologists interested in simulating infection in agent-populations to evaluate public health policy (Willem et al., 2017) . Spatial agent-based models of the spread of measles (Perez & Dragicevic, 2009), influenza (Amouroux et al., 2010; Mao & Bian, 2010; Rakowski et al., 2010; Yang et al., 2011) and cholera (Crooks & Hailegiorgis, 2014) clarify the role of object-oriented and spatially explicit simulations of infectious disease dynamics. Similarly, agent-based approaches to modelling forest insect epidemics (J. H. Anderson et al., 2017; T. Anderson & Dragićević, 2015; Perez & Dragicevic, 2012; Pérez & Dragićević, 2011), and disease transmission across system and scale (Alderton et al., 2015; Bonnell et al., 2010; Braae et al., 2016; Dion et al., 2011; Laperriere et al., 2009; Nunn et al., 2011) are well documented. Willem et al. (2017) outline key epidemiological gaps left by agent-based simulation, including disease re-emergence and theoretical verification. That is, agent-based models, despite their bottom-up emphasis have not be used to understand how endemics re-emerge in new locales. Similarly, their use in verifying epidemiological theory is limited.

Recently, simulation techniques gained popularity during the COVID-19 pandemic. For a number of nation states, public health policy was dependent upon administrative capacity to assess, as well as communicate lockdown, masking, transmission risk (Currie et al., 2020; Nan et al., 2022). Roles which agent-based simulations of disease transmission are well equipped to execute given their geovisual outputs.

2.1.4 Spatial Systems

For effective object-based spatial simulation (S), movement traces, spaces, and places need to be considered. Each element (i.e., the trajectory, the environmental space, and the anthropogenic place) has structural (s) as well as process (p) attributes defining a real-world system (R). Consequently, the expression of *emergent* and continuously occurring spatiotemporal phenomena (P) are observable as animal movement trajectories in geographic space (Gudmundsson et al., 2012; Humphreys, 2009; Roy et al., 2014). Using these terms, computational simulation epistemology is often either: a S, given s of R, to study P of R; or a S, given P, to study s of R (Humphreys, 2004).

Crooks et al. (2008) outline seven challenges for agent-based modelling complex adaptive spatial systems, including validation, defining the purpose of the model, and the extent to which independent theory informs model specifications and parametrization. Similarly, S. Manson et al. (2020) outline open challenges for spatially-explicit agent-based modelling and provide a review of concepts borrowed and shared across economics, ecology, and GIScience for the purpose of modelling spatial systems. Manson et al., also include a comprehensive review for modelling geographic complexity, paying particular attention to how models are evaluated (S. M. Manson, 2007). The capacity to ascribe variable attributes to interacting objects is fundamental to successful spatial simulation (del Mar Delgado et al., 2018). By programming autonomous objects within a model to interact, simulation approaches enable observation and experimentation of how information may behave in dynamic systems (DeAngelis & Diaz, 2019).

2.2 Computational Movement Analysis

Over the past two decades, an exciting subfield within GIScience has emerged. Termed *computational movement analysis*, this subfield extends quantitative approaches to accommodate the now near ubiquitous generation of movement data across two domains – human mobility and animal movement ecology (Ahas et al., 2010; Demsar et al., 2020; Dodge et al., 2016; Gudmundsson et al., 2008, 2012; Laube, 2014; Long et al., 2018; Miller et al., 2019; Zook et al., 2015). As objects are either directly tracked (e.g., GPS traces) or recorded flowing through checkpoints (e.g., camera traps or turnstiles at transit stations), relative positions in space and time are collected near-continuously and at unprecedented spatiotemporal resolutions (Dodge et al., 2008). Such a substantial shift in data generation has fundamentally transformed how various domain experts make sense of movement data (Dodge et al., 2016; Laube, 2015).

The spaces within which and through object movement is modelled can be physical or abstract (Laube, 2014). An appreciation of the considerable breadth of what can be understood as movement in both physical geographic space and abstract space is expressed across computational movement analysis literature (Dodge et al., 2020; Laube, 2014; Long & Nelson, 2013; Long et al., 2018). Laube and Dodge propose new geographic information objects – movement traces (Laube, 2014), and movement data science (Dodge et al., 2020) for coherent computational movement analysis. While GIScience has inherited a largely static worldview from cartography (Laube, 2014), emphasis on information visualisation has given way to information analysis. Therefore, GIS need to be re-envisioned to accommodate a movement trace object oriented data science agenda (Dodge et al., 2020; Laube, 2014; Miller et al., 2019; Purves et al., 2014) which can be better suited for analysing movement traces.

2.2.1 Human Mobility

Human movement through geographic space has been analysed using a variety of approaches. Barbosa et al. (2018) offer a review of quantitative human mobility models and applications ranging from early vehicle surveys and traffic forecasting to more contemporary commuting behaviours and intra-urban movement analysis (Ahas et al., 2010). Barbosa et al. (2018) discuss historical underpinnings of the field, from contextualising geography as spatial interaction (Adey et al., 2014; Barbosa et al., 2018; Ullman et al., 1980); to laws of human migration to explain economic condition, growth, and urban phenomena (Ravenstein, 1885), physical gravity models (Zipf, 1940) to simulate interaction between cities based on distance, and more recently, time geography and simulation (Barbosa et al., 2018; Isaacman et al., 2012; Kwan, 2004; Long & Nelson, 2012) have been used to understand human behaviour. Simulation of human mobility in urban systems have garnered attention across computational sciences, with interesting applications bridging epistemological divides between experiment and simulation (Boldrini & Passarella, 2010; Xu et al., 2021; Yabe et al., 2022).

Advances in human mobility data – that is, the availability and the overall capacity to manage, process, and analyse human movement data at scale – have resulted in effective communication of longstanding GIScience concepts such as the Modifiable Temporal Unit Problem (MTUP) or scale (Su et al., 2022). These innovations however, come with considerable ethical and related geo-privacy hurdles GIScience strives to address (Keßler & McKenzie, 2018). Exacerbating these concerns, many contemporary GeoAI techniques have emerged, including a deep-learning model to consider urban morphological, social, and spatial attributes together (Cornacchia et al., 2020); a dedicated platform for sharing locations within social networks (McKenzie et al., 2022); time-geography approaches to geomasks (Barberousse & Ludwig, 2008); and agent-based simulations incorporating spatial networks (Rosés et al., 2018). Additionally, Shekhar, Feiner, et al. (2015) provide a detailed discussion of opportunities at the intersection of geocomputation and geoprivacy (Shekhar, Feiner, et al., 2015).

2.2.2 Animal Movement Ecology

Computational movement analysis approaches in animal movement ecology focus on movement traces during an individual's lifespan. As such, data and associated methods are oriented to modelling movement in ecological spaces. Resource Selection Function(s) (RSF) are the most commonly used method for linking environmental features to animal location data. Contextualised as habitat selection by individuals, groups, or populations of species, selection functions model paths animals take as they move through a landscape (Thurfjell et al., 2014). As finer-scale extensions of RSF, Step Selection Function(s) (SSF) can be used to consider variation between random possible next steps within a buffer space of a point when adequate spatiotemporal resolution permits.

Hidden Markov Models (HMMs) estimate transition probabilities to query dependence of animal states to their surrounding environment (Michelot et al., 2016; Patterson et al., 2009; Whoriskey et al., 2017). HMMs often accurately determine behaviour selection or behavioural states using movement data (Whoriskey et al., 2017). First-Difference Random Correlated Walks (DRCW) determine complexity underlying animal behaviour states, accounting for temporally-irregularly spaced observations and non-Gaussian errors (Jonsen et al., 2005). Traditionally, state-space approaches (i.e., inferences on what state an individual is based on their spatial attributes and vice verse) have been focused on trajectory data objects (Edelhoff et al., 2016).

Path segmentation methods range in sophistication from simple variable thresholds to algorithmic approaches to breaking apart movement traces into different behavioural components (e.g., sleeping, foraging, idling). Calenge (2006) highlight a variety of approaches to individual animal path segmentation in their foundational (and now almost legacy) R statistical software package (Calenge, 2006). Like path segmentation approaches, a considerable build up of open methods for analysing animal movement data exist (Joo et al., 2020), for example, to analyse trajectories (Long & Nelson, 2013), link locations to environmental data (Dodge et al., 2013), and develop spatial agent-based models (Marshall & Duthie, 2022).

2.3 Movement Space

Following the movement ecology paradigm, wherein animal movement is thought to arise based on interactions between an individuals internal state, motion capacity, navigation capacity, and environmental factors, trajectories of individual movement without environmental linkages provide insight into only one of four key components (Holyoak et al., 2008; Nathan et al., 2008; Neumann et al., 2015). To complement review of movement traces above, I highlight the need for dedicated remote sensing products.

2.3.1 Environmental Linkages

Ecological systems are in a constant state of change (Hastings, 2001; Schlüter et al., 2019). Although non-linear interactions related to ecological dynamism can be modelled using generalized mixed effects models (Hebblewhite & Merrill, 2008), they involve arduous processes when accommodating individual-level heterogeneity of animal behaviour. The most straightforward way to link the dynamism of movement with changing environmental processes is to dynamically represent the environment. For example, using time-series of spectral vegetation indices (Neumann et al., 2015), or Bayesian updating of land-cover (Crowley et al., 2019). Although simulations of dynamism exist, they introduce computational as well as overall model complexity (An et al., 2021). Sub-models of forest dynamism (J. Liu & Ashton, 1998), dynamic airspace allocation (Pellegrini et al., 2020), and land-use change in agrarian (Dai et al., 2020) as well as urban areas (Zhou et al., 2020) are active fields of research.

Alternative approaches to environmental linkage are spurred by growth in bio-logging (Williams et al., 2020) and advances in applied remote sensing (Neumann et al., 2015). These contributions have enabled innovations for collaboration, methods sharing, new opportunities for research combining trajectory and environmental data in exciting ways. For example, Demšar (2022) has innovated a four dimensional approach to combining geomagnetic data with trajectories of long term bird migrations (Iyer et al., 2022) and simulating navigation (Zein et al., 2022).

2.3.2 Biologging

Bio-loggers, devices affixed to animals to study environment or individual physiological characteristics have been used extensively across ecology (Barkley et al., 2020; Payne et al., 2014) and oceanography (Klemas, 2010; Lowerre-Barbieri et al., 2019). Calls for standardizing approaches to bio-logging (Sequeira et al., 2021; Williams et al., 2020) are largely a response to ever cheaper logging devices, availability of voluminous animal movement data; and well-adopted open-data sharing platforms (e.g., movebank; EnvDATA). Similarly, new platforms for continuous, remote, and live monitoring of wildlife (e.g., ICARUS) (Dodge et al., 2013; Kranstauber et al., 2011; Wikelski et al., 2007) foster excitement for animal movement and bio-logging initiatives. For example, 4.8 billion locations across 1288 taxa are available on movebank (Kranstauber et al., 2011) as of November 2023. Movebank also hosts 4.6 billion bio-logged sensor observations.

Potential of these data rests on their incorporation into movement models, wherein environmental linkages can be made directly for each point in space and time. Kays et al. (2015) discuss the potential for bio-logging and animal movement ecology studies as markers of global ecological health. Wilmers et al. (2015) outline the extensive conservation potential for bio-logging to monitor individuals, groups, as well as environmental spaces. While bio-loggers provide remarkable insight into local environmental or biological processes, they may not be a reasonable choice for studies with limited operating budgets (Williams et al., 2020) or hypotheses which could be answered using traditional environmental linkage approaches.

2.3.3 Advanced Applied Remote Sensing

Systems for integrating animal movement trajectories with environmental data are fundamental to relate movement trace to space (Demšar et al., 2015). Remote sensing products – that is, outputs of remote sensing data collection and interpretation – are routinely linked with animal movement trajectories (Dodge et al., 2013; Neumann et al., 2015). As data volume increases, with new sensor and environmental data sources, research questions driving movement ecology studies become increasingly multi-scalar (Neumann et al., 2015), innovative procedures for linking trace and space data are required. For example, Crowley et al. (2019) develop a dynamic representation of wildfire progression using an algorithmic approach - effectively making a dynamic product from a series of static outputs and Bayesian Updating of Land Cover (BULC).

Although trajectories are representations of moving objects, temporal attributes can be lost. For example, images of animal tracks left on snow, or collections of animal droppings, are traces of an individual animals movement through space without temporal information. As rapid chemical processes occur, hyperspectral remote sensing methods can aid in re-attributing time to logged positions (Basille et al., 2014). Hyperspectral techniques peer into chemical composition and process of remote-sensed objects across a wide variety of spatial use cases: sensing fire and fire characteristics (Veraverbeke et al., 2018); geology and mineral exploration (Bedini, 2017); forest biodiversity assessments (Ghiyamat & Shafri, 2010); soil conditions (Yu et al., 2020); and snow and ice properties (Dozier & Painter, 2004).

As individual physiology and behaviour have longstanding linkages, thermal imagery enables researchers the opportunity to remotely sense animal stress prior to slaughter (Sejian et al., 2022); infer animal welfare and physiological state of cattle in milk-production facilities (Fuentes et al., 2021); mange wildlife disease (Rietz et al., 2023); estimate roosting abundance in elusive bats (McCarthy et al., 2021); and of course, detect and track object (individual animal) movement (Havens & Sharp, 2015; Kays et al., 2019; Oishi et al., 2018). Related to thermal imaging individual physiology, McCafferty et al. (2015) outlines challenges for ecologists remote sensing body temperature data to infer stress in avian species.

2.4 Movement Place

This review appends *Movement Place* to the topology offered by Laube (2014), including movement trace and movement space as described above. Movement places capture sociological aspects, which I use to highlight neglected information in the context of socioecological complex adaptive systems (Aswani & Lauer, 2006; Eitzel et al., 2020; Haraway, 2004; Tyler et al., 2007).

2.4.1 Socioecological Complex Adaptive Systems

Coupled socioecological systems operate as places which are important for both animal conservation and human livelihood (Farris et al., 2017; Le et al., 2008). Animals with large home daily ranges often passing through multiple socioecological systems (Chapman et al., 2002; Deygout et al., 2009; Fitterer et al., 2013; Rayfield et al., 2016; Wintle et al., 2005). Animal movements are intrinsically linked to nearly all ecological processes (Williams et al., 2020; Winkler et al., 2014). As animals pass through fuzzy socioecological systems, they become interdependent with socioecological relations (Dragićević, 2010; Le et al., 2008; Wilson et al., 2015). Filatova, Verburg, Parker, and Stannard (2013) outline challenges for agent-based modelling socioecological systems, highlighting design, validation, spatial representation, and integration with existing theoretical models as key areas for future contributions (Filatova et al., 2013).

Socioecological complex adaptive systems definitively involve ongoing and mutable interactions amongst social and environmental components (Cioffi-Revilla, 2016; Tang & Bennett, 2010). Social components – people – are well situated to communicate their context and socioecological relations (Haraway, 2004; Ramanath & Gilbert, 2004). People embedded within socioecological systems have a right to self-determine and define adaptation to address issues (Eitzel et al., 2020; Neeganagwedgin, 2019; Pasternak & King, 2019). For tightly coupled systems, an emphasis on participatory action is critical as local cultural practices are forms of socioecological interaction which collectively inform the capacity for a system to adapt to challenges (An et al., 2021; Poe et al., 2014).

Simulating individual animal-agents as interacting in geographic space enables a readily interpretable and intuitive geo-visual understanding of how changes in socioecological relations may affect animal movements. Such an understanding can guide response to environmental policy as communities face increasing climate variability and rapid social and environmental change (Tyler et al., 2007). I offer the a list of examples to clarify these points. Habitat selection and space use by tigers in south and southeast Asia overlaps considerably with where people live, work, and travel through to maintain their livelihoods (Carter et al., 2013; Imron et al., 2011; Kanagaraj et al., 2013). In the Saami reindeer pastoralism system, Saami express constraints placed by governance structures on herding practice to be the primary limiting factor to maintaining socio-cultural relations with reindeer (Tyler et al., 2007). In the Calakmul Biosphere Reserve, white-lipped peccary are expected to continue their move south into more humid environments. As peccary are an important food source for people in the dry season, prioritizing community determined research objectives (i.e., conducting participatory research) when simulating changing animal movement patterns is critical (Garcı´a-Marmolejo et al., 2015). The same can be said for Saami resisting state-policy, Nepali prioritizing community safety over tiger conservation, and countless other tightly coupled socioecological systems.

2.4.2 Participatory Systems

Distinguishing itself from conventional research methods, participatory mapping and Participatory Geographic Information Systems (PGIS) approaches insist on a substantial change, or reversal, in how power operates during the production of spatial knowledge. To clarify, participatory methods necessarily involve community knowledge and perspectives as core components of research planning and decision-making (Corbett, 2009). Thereby reorienting research from an act done *on* people to an act carried out *with* people. In the case of participatory mapping, this contrast is stark as *who* engages in map-making also defines research priorities, the analysis and representation of information, and the underlying context communicated by the map.

Participatory mapping can be enabled by diverse rationales and can employ a number of mapping techniques, including agent-based modelling (Corbett, 2009; Eitzel et al., 2020). In practice, communities spatialize a collective understanding of their shared geography. It also commonly, and perhaps definitively, emphasizes community-guided research objectives. In contrast, a strict prioritization of data authority sources can be ascribed, in turn, amounts to a denial of people's role in the digital re-contextualization of themselves and their relations (Sieber & Haklay, 2015). Participatory mapping and Participatory Geographic Information Systems, thus, aim to better integrate geographic information available with communities into the decision making process (Sieber & Haklay, 2015).

2.5 Summary

Moving from movement trace to place, this literature review outlines how methods from complex geosimulation and computational movement analysis may be synergistic in enabling innovative agent-based simulations of animal movement ecology. With reference to movement traces, common algorithmic methods for movement simulation are described. Following movement traces, I outlines how movement spaces are conceived in human mobility and animal movement ecology domains as dynamic (urban, ecological, or socioecological) complex adaptive systems. Finally, movement places are discussed as spatial systems with sociological interaction with moving objects. This review serves to introduce a new GeoAI approach to informing an agent-based model of animal movement. Chapter three describes this approach, which uses a relatively simple algorithmic approach to extracting movement rationales to characterize animal-agent behaviour from movement data, and outputs readily-interpretable visualisations of animal space use. While simulations of spatial systems spans a number of geographic domains, agent-based modelling has remained rigid in its dependence on expert-calibrated models.

3 Transferring decision boundaries onto a geographic space

We develop a new spatial artificial intelligence technique for extracting agent rules from animal movement data using classification trees. Often referred to as *movement rationales*, local rules determine how simulated animal-agents interact with space. Agent-space interactions, over time, emerge as trajectories of path selection and represent route selection of a troop of olive baboons (*Papio anubis*). From abstract to discussion, text is formatted as published in Transactions in GIS (https://doi.org/10.1111/tgis.12770). This work was also presented at an IEEE workshop on geospatial visualisation and the ESRI user conference.

3.1 Contribution of Authors

Four authors were involved in this work: Professor Raja Sengupta (RS, McGill University); Professor Liliana Perez (LP, University of Montreal), Jeffrey Katan (JK, MSc. University of Montreal), and myself. As the sole first author, I led this work: conceiving of the idea to extract decision boundaries from a classification tree for the purpose of simulating animal-agent movement, digitizing environmental features, processing movement data, performing path segmentation, building a classification tree, developing behaviour selection surfaces, establishing core components of the agent-based model, and leading all writing efforts.

RS supervised my work and played an active role in discussions related to each aspect of this work including conceptualisation, feature digitization and agent-based modelling. RS played an essential role in encouraging my ideas and best situating them with existing literature. RS also provided critical feedback and helped shape all related research outputs.

LP supervised JK, provided critical discussion for each stage of this work, and ensured prompt publication of our work. LP was instrumental in model conceptualisation, and agent-based modelling aspects of the work. LP also provided valuable and constructive feedback on all outputs.

JK helped with validating environmental feature digitization and improving model performance. JK was an especially valuable contributor as he provided ideas on agent-vision cone modulation, provided critical feedback on writing and figures, and helped prepare the published manuscript for submission.

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3.2 Abstract

We leverage applied machine learning to determine which environmental features are best associated with the "moving" behaviour(s) of a troop of olive baboons (*Papio anubis*; collared with GPS trackers at Mpala Research Centre, Kenya). Specifically, we develop a behaviour-selection surface informed by classification trees trained using movement trajectories and remotely sensed environmental features. Atop this surface, we simulate agent movement towards set destinations, constrained by the relative extent to which sets of features are associated with behaviour(s). To achieve our goal, we perform: (a) path segmentation using thresholding to label training data; (b) agent-rule extraction using classification trees to associate the relative Euclidean distance of a point from environmental features with behaviour; and (c) implementation of this information into an agent-based model to provide a data-driven simulation of troop movement. We believe this framework can accommodate intensification in data velocity, veracity, volume, and variety expected from increasingly sophisticated biologgers and data-fusion techniques.

3.3 Introduction

Animal movement is increasingly being logged and availed using various technologies, ranging across both ecological systems and spatiotemporal scale. For example, as of January 2021, 2.4 billion locations across 1,025 taxa are recorded on movebank.org—a popular open access repository for sharing animal trajectory data (Kranstauber et al., 2011). The availability of these data (both in terms of collection and dissemination) represents potential for new methods to complement traditional techniques for modelling animal movement. Calls for an "integrated science of movement", as well as an "integrated biologging framework", have made clear the continued contribution of geographers to animal movement ecology research. These include data-oriented methods for movement ecology with explicit considerations for geospatial processes, and a broader overlap and methods exchange amongst applied movement domains of human mobility and animal movement ecology (Demsar et al., 2020; Miller et al., 2019; Williams et al., 2020).

Four key components are thought to underlie the movement of individual organisms: (a) internal state; (b) motion capacity; (c) navigation capacity; and (d) external (often contextualized as environmental) factors (Holyoak et al., 2008; Nathan et al., 2008). Motion, navigation, and environmental factors are identifiable via either trajectories, remotely sensed capture of the scene, or a combination of the two. For example, motion manifests as the direction, magnitude, and periodicity of movement, all of which can be extracted from time-series location information (Demšar et al., 2015; Long et al., 2010; Long & Nelson, 2013). Additionally, it is common practice to integrate telemetry-based movement data with spatial datasets (e.g., percentage canopy cover or elevation) to identify external factors affecting movement across environments. Using fine-grained spatiotemporal data, the field has evolved to develop understanding of individual mechanisms (e.g., spatio-cognitive memory and internal time measures) that result in emergent movement patterns and behaviour (Nathan et al., 2008).

In parallel, Agent-Based Model(s) (ABMs) have been developed and designed to model dynamics in complex systems, and are well equipped to explore variation in animal movement patterns, contextualize their linkage to ecological processes, and simulate expected outcomes (Anderson et al., 2017; Bonnell, Chapman, et al., 2016; Bonnell, Ghai, et al., 2016; DeAngelis & Diaz, 2019; Holloway, 2018; Long & Nelson, 2012; Pérez & Dragićević, 2011). Representing dynamics as they relate to individual behaviour and interactions within an environment (including non-linear interactions of the environment and interactions amongst individuals) can be explicit with an agent-based modelling framework. Modelling movement ecology using object-oriented data structures to represent and simulate outcomes resulting from interactions of individuals, conspecifics, sympatric species, and humans is demonstrated by "TIGMOD": an early example of an agent-based movement model with explicit considerations for: (a) space as the primary medium for interaction; and (b) individual heterogeneity (Ahearn et al., 2001). More recently, agent-based models have been developed with the intent of considering contextual information in new ways, and providing alternative simulation methods for animal trajectory data (Anderson et al., 2017; Diaz et al., 2021). Specifically, an African elephant (Loxodonta africanus) spatially explicit agent-based model showcased that simulating high-fidelity trajectories is possible using "a resource-driven model with relatively simple decision rules ...". As well, a Muscovy duck agent-based model was also developed to offer an alternative simulation technique to correlated random walks. Collective decision-making, whereby individual actions lead to the emergence of coordinated movement(s), is an ideal area of research for agent-based modelling frameworks to aid in uncovering how individual interactions and variations in behaviour lead to emergent characteristics (Cook et al., 2020; Hawkes, 2009; Hertel et al., 2020; Kennedy et al., 2014; King & Sueur, 2011).

Agent-based models can be intuitive and readily interpretable simulations of dynamics involved in animal movement (Tang & Bennett, 2010). However, when agent-based simulations of animal movement are implemented, they rely on insights provided by biologists or obtained from the literature. Relying exclusively on expert insight results in two issues: (a) underlying factors cannot be considered separately, as institutionalized ethological and ecological knowledge is interconnected with countless unperceived or understudied phenomena as well as the researcher's worldview; and (b) animal ecology as a field has a historic focus on explicitly natural (as opposed to coupled) systems (Martin et al., 2012). Tight coupling between what are commonly referred to as "human" (or social) and "natural" (or ecological) systems has been documented across fields. Geographic Information Science (GIScience) researchers working in social and ecological science domains have clarified systems coupling using common terms rooted in complex systems science (Bennett & McGinnis, 2008; Cenek & Franklin, 2017; Liu et al., 2007). Fundamentally, animal movement (research) is not divorced from human interpretation, human behaviour or interaction, perception of the environment, and/or environmental policy (Cresswell, 2011, 2012, 2014; Semeniuk et al., 2010). The importance of explicitly considering tight coupling of natural and social systems is reinforced as well-informed wildlife policy often inadvertently regulates human livelihoods (Beaumier et al., 2015; Bennett & McGinnis, 2008; Liu et al., 2007; Perez et al., 2018; Tyrrell, 2007). Agent-based models can provide a framework for understanding animal movement as a key emergent characteristic of socio-ecological complex adaptive systems. Finally, as agent-based models are often spatially explicit, integration is generally possible with any information that can be spatialized and digitized into a Geographic Information System (GIS). Our method aims to provide a core component of an adaptive agent-based movement ecology model that can appropriately consider and integrate various forms of spatial information.

Algorithmic methods can offer considerable advantages when extracting movement rationales from environmental or trajectory data. For example tree-based algorithms, like classification and regression trees, can be used to enable modelling frameworks that make no assumptions about how embedded processes become observable data; nor do they require extensive pre-processing steps or data transformations (Breiman, 2001). Classification trees are recursive algorithms ideally suited to explore data structures as well as analyse complex ecological data (Loh, 2011). Interesting work using such technologies to identify potential environmental factors underlying animal movement, determine population distributions, or predict zoonotic disease transmission risk is already well documented (Ahearn et al., 2017; Elith et al., 2008; Han et al., 2015; Leathwick et al., 2006;

Oloo & Wallentin, 2017; Torrens et al., 2011; Ward et al., 2016). With respect to using these technologies to inform agent-based models, notable examples include: context-sensitive random walks that incorporate local external factors to simulate the movement of tigers at Royal Chitwan National Park in Nepal (Ahearn et al., 2001); genetic algorithms to simulate representative relative-turn angles and step-distance of homing pigeons (Oloo & Wallentin, 2017); reinforcement learning to contextualize the risk and reward of agent behaviour (Sutton & Barto, 1999; Tang & Bennett, 2010); and artificial neural networks to assign weights to link environmental features to an agent's internal spatially explicit map of its surroundings (Huse et al., 1999; Strand et al., 2002).

To demonstrate how algorithmic methods can uncover and explicitly consider environmental features as external factors underlying animal movement, we use two simple artificial intelligence technologies: (a) classification trees to extract rules that associate behaviours with environmental features; and (b) agent-based modelling to build a bottom-up simulation of movement based on extracted rules and environmental heterogeneity. Showcasing how high spatiotemporal trajectory data allow for decision boundaries in classification trees tobe transferred onto a continuous surface for agent simulation is the core objective of this article.

3.4 Methods

Strandburg-Peshkin et al. (2015) obtained data from 26 olive baboons (14 adults, 10 subadults, and 2 large juveniles) with GPS collars (e-Obs Digital Telemetry, Gruenwald, German; with a reported average positional error of 0.26 m) between 1 and 14 August 2012 in collaboration with the Mpala Research Centre, Laikipia Plateau, Kenya. The locations of these olive baboons were logged with a relatively high temporal frequency (1 Hz: 1 record per second) continuously during daytime hours, from 0600 to 1,800 hr local time. We obtained this data from Movebank (ID: 7023252) (Strandburg-Peshkin et al., 2015). The study description noted that not all GPS collars transmitted location data successfully throughout each day, resulting in 10 million observations of individual baboon locations. We cleaned and spatially projected the collected trajectories with tools provided in the tidyverse, lubridate, sp, and rgdal packages for R, removing 5,758 missing observations (of 10,402,385 total observations; 0.054) and projecting trajectories to Universal Transverse Mercator (UTM) zone 37 North for Mpala, Kenya (R. Bivand et al., 2015; R. S. Bivand et al., 2013; R Core Team, 2020; Wickham et al., 2019). We set aside days 3, 6, 9, and 11 and do not include these trajectories in building our classification tree or parameterizing the agent-based model. Keeping entire days as validation (as opposed to a random sample) enables more meaningful tests of our simulation. Specifically, as the troop visit different destination sites throughout the 2-week period, keeping multiple days aside provides validation across different destinations. Figure 1 shows the observed trajectories of the olive baboon troop at Mpala Research Centre in Laikipia, Kenya.

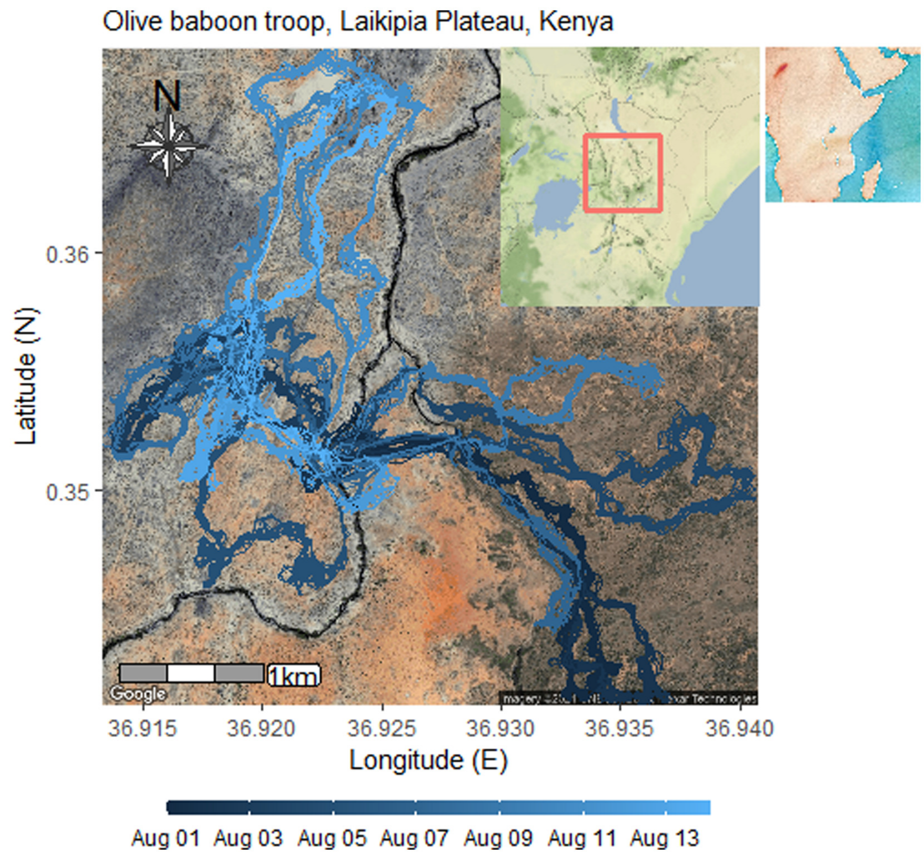

Figure 1: Olive baboon (Papio anubis) trajectories collected at the Mpala Research Centre in Kenya are displayed with a blue gradient denoting time. Google imagery used for satellite and Kenya inset maps. Stamen watercolour imagery used for regional inset map of Africa

We extract environmental features from the scene (using a normalized difference vegetation index to define vegetation and clearings, and on-screen digitization for human trails and the river network), which we contextualize as external factors underlying behaviour selection (and therefore animal movement). Using Operational Land Imager imagery aboard Landsat 8 (dated 26 October 2018) and Google Earth/Digital Globe imagery (dated 25 June 2012), we identified four environmental features: clearings (or open areas); the river; trees; and a regional network of human-made trails. Strandburg-Peshkin et al. (2015) identified road-following and short-range avoidance of dense vegetation as possible environmental factors underlying path selection of the troop. Although innovative remote sensing products exist to further identify features, we use just these four readily identifiable features to help demonstrate and highlight the key contribution of this work: a framework for agent-based modelling that explicitly considers environmental heterogeneity as well as uncertainty in unambiguous ways to model path selection. To link trajectory and environmental information, we calculate the Euclidean distance between environmental features and each GPS logged position. This expression of environmental heterogeneity (at each point) was then linked with different (theoretical) behavioural states of the animal using path segmentation (Edelhoff et al., 2016). The statistical signal provided with this linkage is reduced to the spatial resolution of environmental features (i.e., 3 m spatial resolution of remote sensing products used to collect features).

We threshold our trajectories into two broad behaviour states: moving and sedentary. To perform this segmentation, we use the adehabitat package for R to collect physical characteristics at each logged position (Calenge, 2006). Specifically, we consider that any positions with velocity greater than 3 m/s indicate moving behaviours. Sedentary points, those recorded with velocity below 3 m/s, are in a category of behaviours which would require improved spatial resolution of environmental features to extract decision boundaries (relevant to sedentary behaviours). We are only able to consider velocity with such ease due to GPS positions having been logged at a relatively high temporal resolution (1/s). To clarify, our environmental raster layers' spatial resolution is 3 m. And when individual baboons are moving at less than 3 m/s, we cannot make clear associations with environmental data. Of the logged positions in the training dataset, 32,707 observations occurred while baboons in the troop were travelling at greater than 3 m/s. To maintain class balance, we generate 32,707 new random points within the bounding box of troop movements—the equivalent of a "null" model. Figure 2 shows the resultant classification tree.

We use this subset (both null and moving points, 64,000 observations) to build a classification tree using sci-kit learn (Pedregosa et al., 2011). Our classification tree is parameterized using the Gini impurity as the splitting criterion, a minimum sample size of 20 observations, a maximum depth of five layers, and a minimum impurity decrease of $1e^{-7}$. Each split (of the tree) or partition (in data) only occurs if the Gini impurity decreases by at least $1e^{-7}$ units. It stops splitting once nodes have fewer than 20 observations ("samples"), or once the tree reaches a depth of five layers.

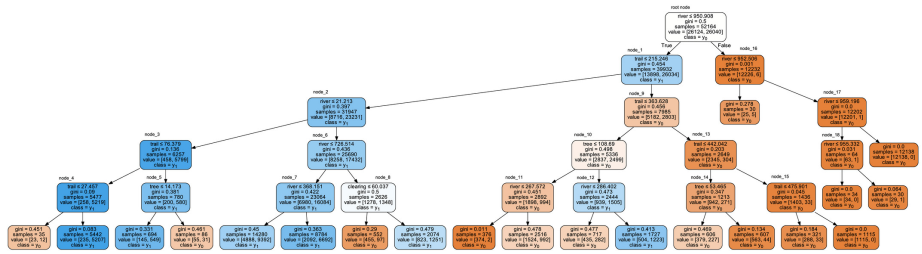

Figure 2: Classification tree with depth of 5; minimum sample size of 20 observations; minimum Gini impurity decrease by $1e^{-7}$ units

These stoppage conditions are common "pruning" techniques for classification and regression trees (Fournier & Crémilleux, 2000). Without these parameters, default values allow the tree to keep building until it has overfit to training data (e.g., default for minimum impurity split is 0, meaning subset data would not need to become more "pure" to continue splitting). The classification tree queries data with partition rules, then selects partitions that result in a maximum decrease in impurity. Subset impurity must decrease iteratively for the classification tree to be working. That is, the perceived homogeneity of subsets must increase as they move down the classification tree. This is due to the underlying algorithmic structure of (any type of) binary tree(s). The tree only continues if its understanding of how to best classify data is improving. Here, the quantifiable metric being minimized is the Gini impurity (as opposed to entropy or other measures in the applied machine learning literature).

Each node of the tree represents a classification made as part of iterative partitions of data. As well, nodes provide a relative expression of uncertainty (as the complement of the nodal Gini impurity). Blue nodes suggest the classification tree interprets its input as a signal for movement. Orange nodes suggest the tree interprets, and would classify, points as null if further iterations are not possible. Local decision boundaries expressed by the tree are unidirectional and unidimensional; nodal partition rules utilize only one logical operator ($\leq$) and apply to only one feature per iteration. Collectively, the classification tree is an algorithmic expression of how to optimally label observed points, based on environmental heterogeneity, as either "moving" or not. This algorithmic expression is often visualized as a binary tree, since querying a single feature using "$\leq$" organizes data into at most two child subsets. For example, in Figure 2, node1 categorizes each point as either being 215.246 m or not from the edge of the trail feature. The tree selects this specific partition as its search found this decision boundary to maximize the homogeneity of its child subsets (node2 and node9). In our implementation, classification functions iteratively organize as many "moving" points together as possible. A core relation to behaviour is being made on the basis that training data provided to the classification tree are reflective of ecological reality. And that "moving"-type behaviours are a meaningful conceptualization with respect to olive baboon ethology and ecology.

To consider these nodal rules and their associated information in aggregate, we rasterize each local decision boundary. We take the complement of the Gini impurity, to quantify the relative homogeneity result of the partition. This complement is a measure of certainty being expressed at the node. The more impure subset datasets are, the less certainty the rule can offer in classifying points. Aggregated, this becomes an understanding of certainty of classifying data as "moving" based on the relative distance a point is from key environmental features at the regional (in terms of geography) and global (in terms of computation) scale. To arrive at a spatially explicit surface, we rasterize each partition rule based on nodal information. Specifically, the distance to an environmental feature, nodal Gini impurity, and partition threshold are considered to transfer decision boundaries onto a geographic space in the following way:

$$Desirability\ (movement\ selection) = (1 - G),\ if\ dE \leq pt$$

$$Uncertainty\ (null\ selection) = -(1 - G),\ if\ dE > pt$$

When the partition rule is "True", that is, when points are within the specified distance of the environmental feature that is being partitioned, we ascribe a weighting based on the complement of the Gini impurity at the specified node. If the signal provided to the training data reflects ecological reality, this surface expression is a spatially explicit consideration of environmental heterogeneity and its influence on behaviour selection. In the simplest terms, our derived behaviour selection is an understanding of where the troop would engage in any "moving" or ">3 m/s" behaviours. Uncertainty selection, expressed as the additive inverse of the complement of the Gini impurity, $-(1-G)$, is used when the classification tree organizes data as not belonging to "moving" behaviours. Since both local movement and null selection are communicated via nodal information, we aggregate the complement $(1 - G)$ to reflect movement selection, and the additive inverse of the complement $-(1 - G)$ to reflect uncertainty. Figures 3 and 4 reflect standardized aggregations of these rasters, which we term "Desirability" and "Uncertainty" selection surfaces. Sedentary points are reflected in "patches" of uncertainty in Figure 4, as the expression of environmental heterogeneity here suggests null selection (and sedentary behaviours are likely to belong to null selection within the classification tree). As a careful note, the classification tree is not able to classify points as sedentary; it is only able to classify when environmental heterogeneity is thought to be capable of facilitating moving behaviours. For example, if a known sedentary point is provided to our classification tree, the outputs will express a relatively high measure of how uncertain it is in classifying the observation. The aggregated spatially explicit decision boundaries related to "moving" classification are expressed as a movement behaviour selection surface. For "null" classification, the surface reflects uncertain behaviour selection. Both surfaces are then standardized to maintain their distribution, while ranging from 0 to 1 (Figures 3 and 4). As such, the negative directionality of uncertain behaviour selection is recontextualized such that higher uncertainty values indicate points where the classification tree is relatively unsure of its classification of observations as belonging to "moving" behaviours. Atop these behaviour selection surfaces, we simulate agents representing baboons ("baboon-agents") to navigate between presumed sleeping sites and destinations.

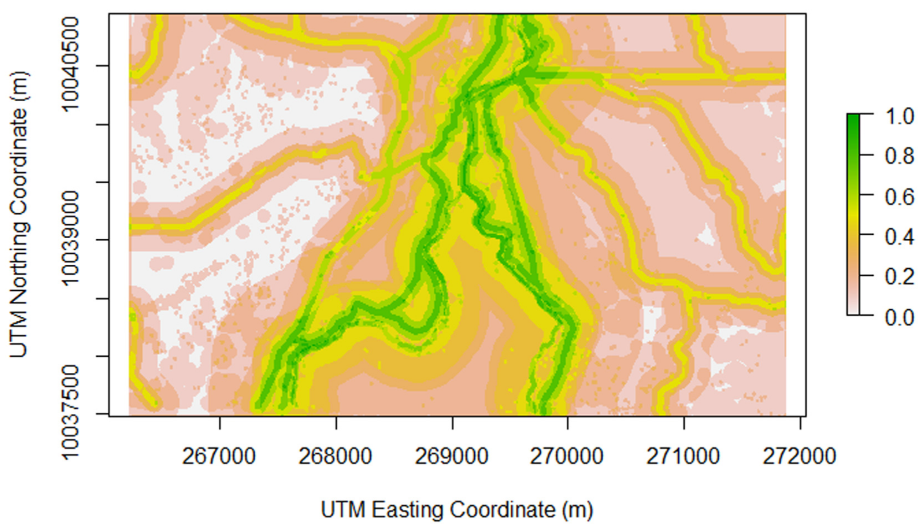

Figure 3: Movement selection surface for troop of olive baboons observed during 1–14 August 2012 at Mpala Research Centre, Kenya. Green indicates areas that express environmental heterogeneity; the classification tree interprets these as spaces likely to facilitate "moving" behaviours. This surface is queried by baboon-agents for movement-related decision-making

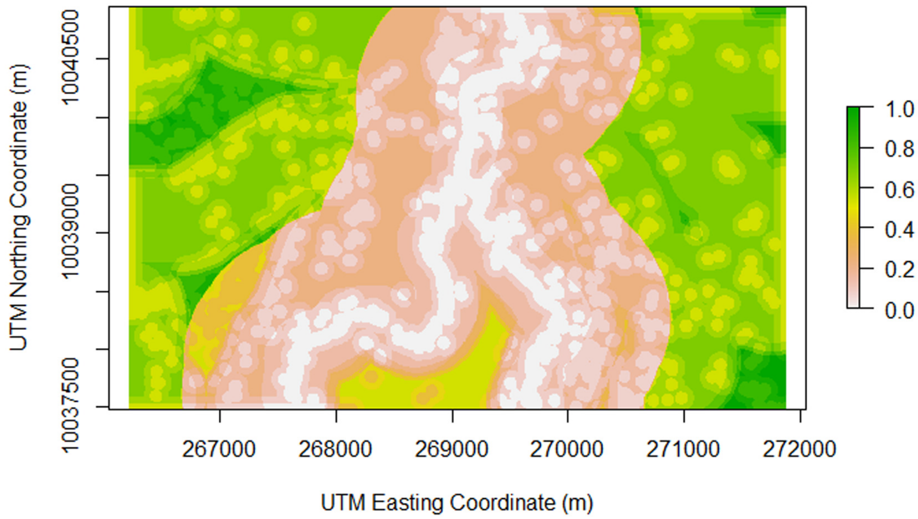

Figure 4: Uncertain or null selection surface for troop of olive baboons observed during 1–14 August 2012 at Mpala Research Centre, Kenya. Green indicates areas that express environmental heterogeneity; the classification tree interprets these spaces as likely to facilitate sedentary or "other" behaviours. This surface is queried by baboon-agents for vision cone modulation

Table 1: Internal movement logic of baboon-agents

I	Face destination
II	Check movement and uncertain selection surface values within the agent vision cone
III	Take one step towards the cell with greatest movement selection value
IV	Modulate agent vision cone by uncertainty
V	If location has not changed over previous timesteps, take one step directly towards the destination

We develop our agent-based model using NetLogo (and provide its internal logic in Table 1) as it is an easy-to-use multi-agent modelling environment that can incorporate raster datasets. The model consists of one agent representing an individual baboon moving between the origin and user-set destinations. The origin and destinations were selected using kernel density estimation of sedentary segments of observed trajectories. After facing a user-set destination, baboon-agents query the movement selection surface within a 230° vision cone and depth of four cells. This angle and depth are also user-set but are then modulated by uncertainty expressed by the null selection surface. We used 230° as the relative angle within moving segments of observed trajectories fell within ± 2 rad (4 rad 230°). This could be an artifact of moving behaviours as they invariably have some component of directionality, or high-temporal resolution. We maintain a relatively crude understanding of directionality in our model to test the utility of selection surfaces informed by classification trees. To initiate agent movement from a starting position to an intended destination, baboon-agents query the movement selection surface within their vision cone and select the cell with the highest "movement selection". Based on uncertainty expressed at that cell, the baboon-agent vision cone angle is multiplied by a factor of $(1 - Uncertainty)$, and the vision cone depth by a factor of $(1 + Uncertainty)$. Uncertainty, or null selection, here is connected to "not moving" and presumably low directionality behaviours. We also set two optional conditions which direct baboon-agents to resolve movement decisions by taking one step directly towards the destination when too many paths lead to "dead ends" (baboon-agent has moved <11 units in last 25 ticks); or when too few options force baboon-agents to continuously retrace their paths (baboon-agent has moved <1.4 units in last 5 ticks). The spatial resolution of the agent model is 6.5 m, with temporal resolution 20 s; thus baboon-agents move at an average velocity of 0.325 m/s. To provide an ensemble of movement behaviour, we run our model 100 times for each day. As an important note, our model does not incorporate time beyond using velocity to discern training moving behaviours. Our framework for "transferring decision boundaries onto a geographic space" is visualized in Figure 5.

3.5 Results

Our procedure demonstrates how large spatiotemporal datasets with high temporal granularity can aid in developing simulations of dynamics underlying animal movement. Specifically, we show how environmental features can be explicitly incorporated into the internal movement logic of agent-based models. There are two key steps to our procedure: first, the extraction of agent rules from trajectory and environmental feature data; then, incorporation of this extracted information into an agent model. Extracted information for agent rules (or movement rationales) is in the form of the internal data partitions classification trees use to discern between "moving" and uncertain (or null selection) behaviours—commonly referred to as decision boundaries. These decision boundaries are aggregated into a surface atop which agents are simulated to move towards set destinations.

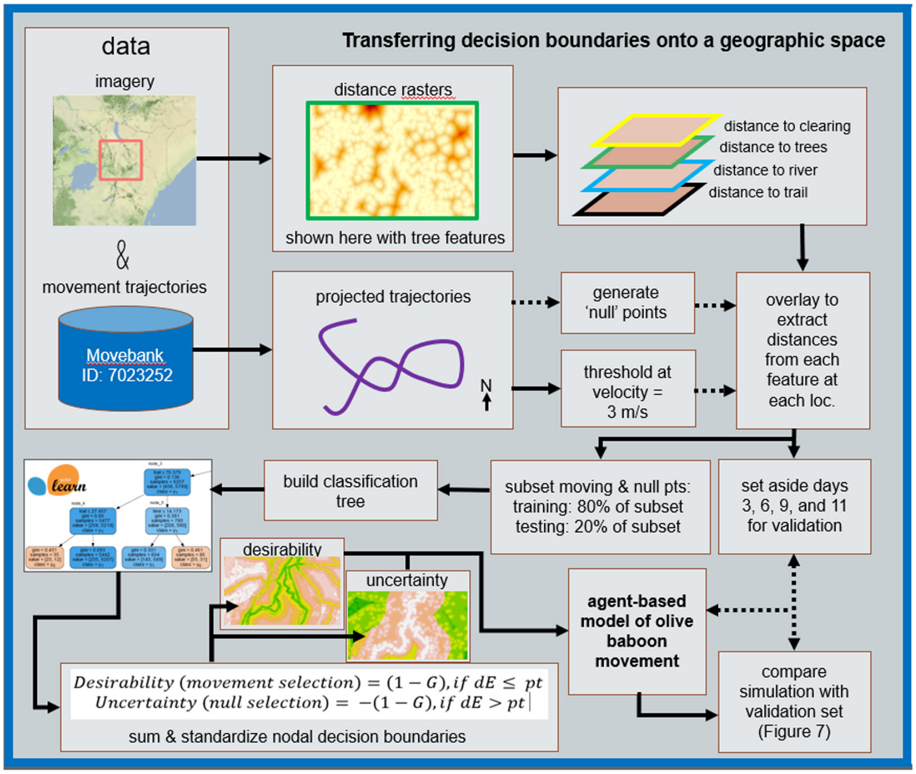

Figure 5: Framework for transferring decision boundaries found in classification trees onto a geographic space for spatially explicit agent-based modelling movement

With respect to the first (information extraction) step, our classification tree achieved a classification accuracy of 80%, classification error of 20%, and sensitivity of 0.937. We interpret these results as an indication that the classification tree can discern and correctly identify moving points 80% of the time when provided with unseen point data with linkages to environmental features. Figure 2 is a visualization of the classification tree. Figure 5 describes how the output from the tree is handled, as well as how this technology is used in our framework.

With respect to the second (information implementation) step, our agent-based model is visualized in Figure 6 along with a kernel density estimate of observed trajectories. The origin, daily destinations, and a river crossing site are labelled. This river crossing site is a visibly important site in animations of troop trajectories, and interestingly is also picked up as a unique site for movement in simulations. The proximity of simulated runs to observed trajectories, as well as the frequency with which the simulation preferred a certain path, are shown in Figure 7.

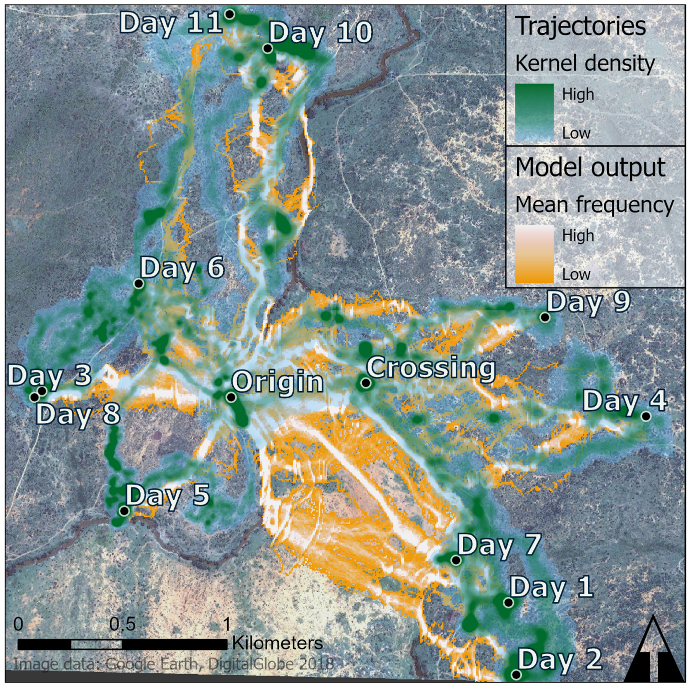

Figure 6: Agent-based model simulation outputs visualized by frequency (in orange) along with kernel density estimations of observed olive baboon trajectories (in green). Note river crossing feature, which was apparent as a unique point for movement in both observed trajectories and simulation output. Basemap imagery provided by Digital Globe, Google Earth™

For each day, we calculated the Euclidean distance from the trajectory data and superimposed it with the frequency output from our agent-based model. The distribution of movement selection values in the frequency output map has a very strong right skewness. So, we used a natural log transformation, followed by a linear rescaling, so that all days had the same range, resulting in 10 frequency classes. We were then able to compare, by location, the relation between the frequency map and its proximity to trajectory data. Figure 7 shows this validation effort, reasonably replicating real trajectories for days 9 and 11. The observed troop frequents multiple destinations each day throughout the 2-week data period, but especially on days 3 and 6 the troop stays in a relatively small area for most of the day. For such days, because of the way destinations are handled in our agent model (i.e., a single static destination is user-set for each day), outputs show simulated

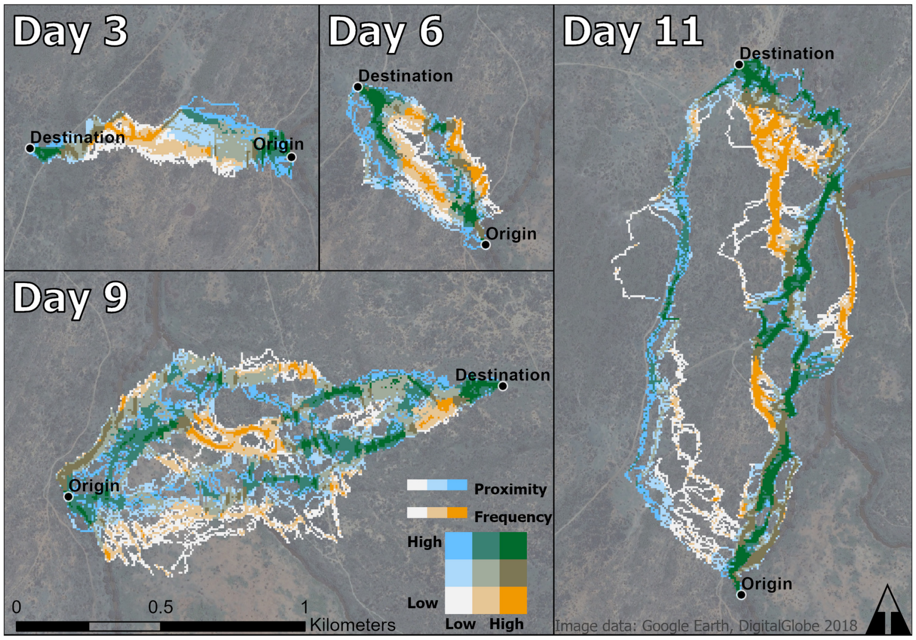

Figure 7: Agent-based model simulation outputs for validation days (3, 6, 9, and 11) visualized by frequency (in orange) and proximity to observed trajectories (in blue). Path selection highlighted by green indicates agreement between observed olive baboon movements and baboon-agent trajectories. Basemap imagery is provided by Digital Globe, Google Earth™

trajectories taking a "shortcut" to final destinations, instead of the more circuitous route real olive baboons took in the region.

While visually comparing the simulated and observed trajectories is helpful, they do not provide a measure of the overall performance of our model. An alternative is to quantify the deviation (as distance) between simulated and observed trajectories. The variation of distance between observed and simulated trajectory is dependent on the distance between destinations and sleeping sites, which varied greatly between each day; the further the destination, the farther "off-track" an agent could go. To better compare performance between days, the mean distance between simulation and observation of each day was rescaled by the maximum distance for that day, such that the maximum for all days is 1. Figure 8 plots these deviations for each simulated day. Here, high-frequency classes represent the cells that simulated trajectories often pass through. Low-frequency classes were relatively unfrequented cells. The trend-line plotted with ±1 standard deviations

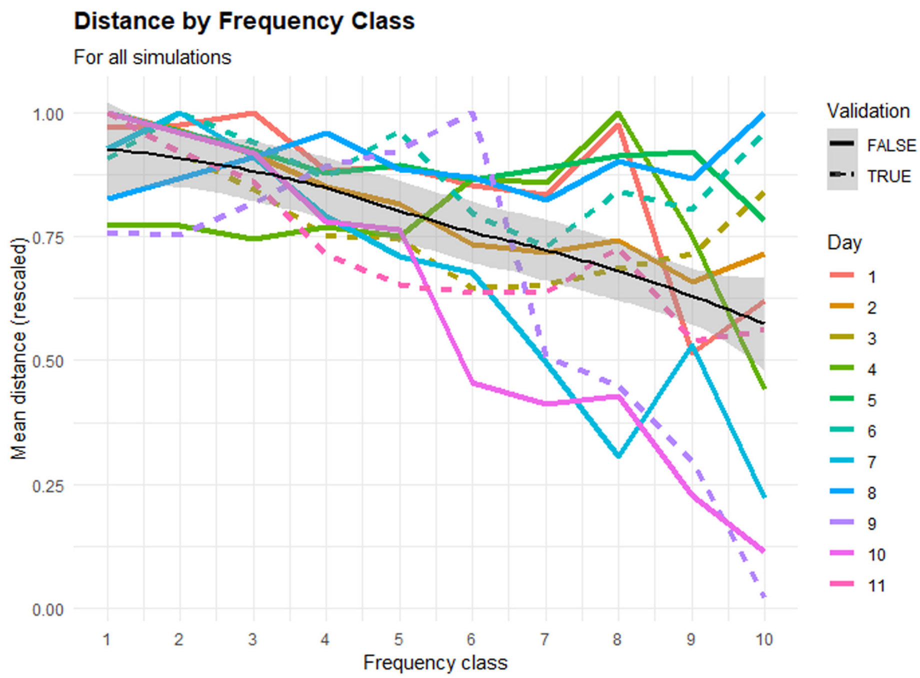

Figure 8: Deviation of each frequency class from observed trajectories. Lower mean distance values (y-axis) indicate overlap between observed trajectories and simulations. These values are rescaled and are a relative measure of distance. Frequency classes denote categories of cells visited by simulated trajectories, and how often trajectories use the cell. Validation days are highlighted using dashed lines. Validation days 9 and 11 deviate less than the average of all days

represents an average, which improves as we consider where there are more simulated trajectories. Validation days are represented with dashed lines and confirm what Figure 6 suggested—that days 9 and 11 performed best. In other words, our framework produced simulations where baboon-agents travelled the same spaces as observed trajectories.

3.6 Discussion

Agent-based models have been used extensively to explore the impact of animal movement patterns across space and time and predict environmental outcomes. Movement rationales expressed in such models have often been based on expert knowledge about the behaviour of the species of interest (Bonnell, Chapman, et al., 2016). While neglecting input from behavioural ecologists would be disingenuous, considerable surveillance bias in animal ecology provides impetus for methods that can accommodate local knowledge as well as intensifications in data velocity, veracity, volume, and variety expected from increasingly sophisticated biologgers and data-fusion techniques (Boyce, 2006; Hebblewhite & Haydon, 2010; Martin et al., 2012; Stallknecht, 2007).

Here we have demonstrated that a large spatiotemporal dataset with high temporal granularity can be used to: (a) develop a surface to highlight environment-related selection of movement; and (b) programme an agent-based model that uses the behaviour selection surface in combination with simple rules of motion to simulate troop movements. This fits well within the broader area of work GIScientists are engaging in towards an integrated science of movement (Miller et al., 2019; Williams et al., 2020). With evermore sophisticated biologgers and data-fusion techniques there will continue to be a rapid rise in volumes of valuable movement data. Our work indicates that there is an opportunity to develop widely applicable methods to use such datasets, extract location-specific movement behaviours, and convert and explicitly consider this information in agent-based modelling frameworks.

Simulations using the described procedure could be tested against expert knowledge rationales regarding preferred habitats, avoidance of high-risk predator or disease areas, territorial defence, social behaviour, or weighted combinations of these rationales. For example, in Where the animals go, this troop's description suggests trajectories were collected over a 4-week period (Cheshire & Uberti, 2017). Additionally, in these unseen data, there was report of a leopard which affected troop sleeping site selection after 14 August. This unseen data could serve as further validation; our framework could be adapted to test how simulations perform under these unique conditions. Such an approach could augment expert interpretation to decipher an understanding of components underlying movement behaviour selection.

While the current procedure is demonstrated with a single classification tree, it could be scaled using ensemble techniques to consider and weight the different spaces where and times when moving groups of animals might engage in specific behaviour (e.g., seasonal drought and changes in vegetation characteristics influencing foraging behaviour). Our framework could accommodate other established representations of animal movement (like context-specific random walks) in conjunction with information from probability and uncertainty surfaces to determine path selection. The core contribution of our methodological framework is the transfer of decision boundaries explicitly expressed by classification trees onto a geographic space. Inherent aspects of this space include socio-cultural relations people have with animals, as well as embeddedness of socio-ecological complex adaptive systems. Exciting work on collecting and spatializing local knowledge suggests a wide variety of features (e.g., constructed fences, known migration routes or hunting sites) could be incorporated into our approach (Aswani & Lauer, 2006)—as long as they are ascribed spatiality in a GIS. Agent-based models, when informed by data-driven methods, are unique tools that can accommodate voluminous data with unknown or inconsistent veracity and velocity, as well as explicitly incorporate spatiality of local knowledge. There are two reasons for the overall flexibility of our approach: (a) classification trees' capacity to handleexplanatory variables without data transformations; and (b) the spatially explicit nature of our agent-based modelling platform. For example, gradient descent using boosted classification trees could be used to reduce the relative "sharpness" or abruptness visible in Figures 3 and 4, and new environmental features could be identified and characterized using innovative remote sensing and hyperspectral processing technologies. The agent's logic could also be improved in future work. For example, incorporating viewshed analysis into the vision cone modulation would add towards recreating simulations of how troops determine where to go. Cost weighting, informed by either landscape genetics or geographic phenomena (such as urbanization or elevation), could be incorporated into classification tree(s) as features to influence selection surfaces; or explicitly in an agent's internal logic (e.g., for elevation, additional cost surfaces could be fed into what information an agent is considering before moving). Finally, to reduce the determinism of our model, we could programme agents to select from a range of high-valued movement cells at random. Instead, our efforts focused on testing the informativeness of selection surfaces.

While our model adequately replicates movement behaviour selection, there has been other research in movement ecology that looks to identify behaviours within the environments in which they occur. For example, "path segmentation" refers to changes recorded in an animal's movement behaviour based on observed trajectories (Edelhoff et al., 2016). Associated methods quantitatively describe the geometric properties or physical characteristics of trajectories, which combined with time-series analysis methods can indicate changes in behaviour state. Further, innovative methods exist that could be considered for segmenting animal movement trajectories, including pattern mining and behavioural change point analysis (Zhang et al., 2019). The research questions commonly addressed using path segmentation methods include: (a) quantitative description of movement patterns; (b) detection of significant change points; and (c) identification of underlying processes/hidden states. Of the latter, state-space models (e.g., hidden Markov models [HMMs]) can be built to estimate transition probabilities and test whether switching between states depends on certain habitat characteristics (Whoriskey et al., 2017). Other models, such as advanced first-difference random correlated walk (DCRW), go further by determining the complexity underlying behavioural states, and also account for temporally irregularly spaced observations and non-Gaussian errors (Jonsen et al., 2005). Admittedly, such frameworks necessarily incorporate linkages due to time—something our model does not do. However, an ensemble approach that weights information from trees based on when environmental features and trajectories are collected could function within this framework as an adequate representation of time. Interesting work using conceptualizations surrounding space-time prisms has also been demonstrated in a spatially explicit agent-based movement model (Loraamm, 2020). Methods demonstrated here are a foundation to understand the influence of environmental heterogeneity on behaviour selection. And could be understood as a tool within a broader toolkit for agent-based modelling movement ecology.

Manuscript References

Ahearn, S. C., Dodge, S., Simcharoen, A., Xavier, G., & Smith, J. L. (2017). A context-sensitive correlated random walk: A new simulation model for movement. *International Journal of Geographical Information Science*, *31*(5), 867–883.

Ahearn, S. C., Smith, J. L. D., Joshi, A. R., & Ding, J. (2001). Tigmod: An individual-based spatially explicit model for simulating tiger/human interaction in multiple use forests. *Ecological Modelling*, *140*(1-2), 81–97.

Anderson, J. H., Downs, J. A., Loraamm, R., & Reader, S. (2017). Agent-based simulation of muscovy duck movements using observed habitat transition and distance frequencies. *Computers, Environment and Urban Systems*, *61*, 49–55.

Aswani, S., & Lauer, M. (2006). Incorporating fishermen's local knowledge and behavior into geographical information systems (gis) for designing marine protected areas in oceania. *Human organization*, *65*(1), 81–102.

Beaumier, M. C., Ford, J. D., & Tagalik, S. (2015). The food security of inuit women in arviat, nunavut: The role of socio-economic factors and climate change. *Polar Record*, *51*(5), 550–559.

Bennett, D., & McGinnis, D. (2008). Coupled and complex: Human–environment interaction in the greater yellowstone ecosystem, usa. *Geoforum*, *39*(2), 833–845.

Bivand, R., Keitt, T., Rowlingson, B., Pebesma, E., Sumner, M., Hijmans, R., Rouault, E., & Bivand, M. R. (2015). Package 'rgdal'.

Bivand, R. S., Pebesma, E., Gómez-Rubio, V., et al. (2013). Applied spatial data analysis with r. *Springer Mathematics and Statistics eBooks 2013 English/International*.

Bonnell, T. R., Chapman, C. A., & Sengupta, R. (2016). Interaction between scale and scheduling choices in simulations of spatial agents. *International Journal of Geographical Information Science*, *30*(10), 2075–2088.

Bonnell, T. R., Ghai, R. R., Goldberg, T. L., Sengupta, R., & Chapman, C. A. (2016). Spatial patterns of persistence for environmentally transmitted parasites: Effects of regional climate and local landscape. *Ecological Modelling*, *338*, 78–89.

Boyce, M. S. (2006). Scale for resource selection functions. *Diversity and distributions*, *12*(3), 269–276.

Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). *Statistical science*, *16*(3), 199–231.

Calenge, C. (2006). The package "adehabitat" for the r software: A tool for the analysis of space and habitat use by animals.

Cenek, M., & Franklin, M. (2017). An adaptable agent-based model for guiding multi-species pacific salmon fisheries management within a ses framework. *Ecological Modelling*, *360*, 132–149.

Cheshire, J., & Uberti, O. (2017). *Where the animals go: Tracking wildlife with technology in 50 maps and graphics*. WW Norton New York.

Cook, C. N., Lemanski, N. J., Mosqueiro, T., Ozturk, C., Gadau, J., Pinter-Wollman, N., & Smith, B. H. (2020). Individual learning phenotypes drive collective behavior. *Proceedings of the National Academy of Sciences*, *117*(30), 17949–17956.

Cresswell, T. (2011). Mobilities i: Catching up. *Progress in human geography*, *35*(4), 550–558.

Cresswell, T. (2012). Mobilities ii: Still. *Progress in human geography*, *36*(5), 645–653.

Cresswell, T. (2014). Mobilities iii: Moving on. *Progress in Human Geography*, *38*(5), 712–721.

DeAngelis, D. L., & Diaz, S. G. (2019). Decision-making in agent-based modeling: A current review and future prospectus. *Frontiers in Ecology and Evolution*, *6*, 237.

Demsar, U., Long, J., & Sila-Nowicka, K. (2020). Integrated science of movement. *Journal of Spatial Information Science*, *21*, 25–31. https://doi.org/10.5311/JOSIS.2020.21.721

Demšar, U., Buchin, K., Cagnacci, F., Safi, K., Speckmann, B., Van de Weghe, N., Weiskopf, D., & Weibel, R. (2015). Analysis and visualisation of movement: An interdisciplinary review. *Movement ecology*, *3*(1), 1–24.

Diaz, S. G., DeAngelis, D. L., Gaines, M. S., Purdon, A., Mole, M. A., & van Aarde, R. J. (2021). Development and validation of a spatially-explicit agent-based model for space utilization by african savanna elephants (loxodonta africana) based on determinants of movement. *Ecological modelling*, *447*, 109499.

Edelhoff, H., Signer, J., & Balkenhol, N. (2016). Path segmentation for beginners: An overview of current methods for detecting changes in animal movement patterns. *Movement ecology*, *4*(1), 1–21.

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of animal ecology*, *77*(4), 802–813.

Fournier, D., & Crémilleux, B. (2000). Using impurity and depth for decision trees pruning. *Proceedings of the Second International ICSC Symposium on Engineering of Intelligent Systems*.

Han, B. A., Schmidt, J. P., Bowden, S. E., & Drake, J. M. (2015). Rodent reservoirs of future zoonotic diseases. *Proceedings of the National Academy of Sciences*, *112*(22), 7039–7044.

Hawkes, C. (2009). Linking movement behaviour, dispersal and population processes: Is individual variation a key? *Journal of Animal Ecology*, *78*(5), 894–906.

Hebblewhite, M., & Haydon, D. T. (2010). Distinguishing technology from biology: A critical review of the use of gps telemetry data in ecology. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1550), 2303–2312.

Hertel, A. G., Niemelä, P. T., Dingemanse, N. J., & Mueller, T. (2020). A guide for studying among-individual behavioral variation from movement data in the wild. *Movement Ecology*, *8*(1), 1–18.

Holloway, P. (2018). Simulating movement-related resource dynamics to improve species distribution models: A case study with oilbirds in northern south america. *The Professional Geographer*, *70*(4), 528–540.

Holyoak, M., Casagrandi, R., Nathan, R., Revilla, E., & Spiegel, O. (2008). Trends and missing parts in the study of movement ecology. *Proceedings of the National Academy of Sciences*, *105*(49), 19060–19065.

Huse, G., Strand, E., & Giske, J. (1999). Implementing behaviour in individual-based models using neural networks and genetic algorithms. *Evolutionary Ecology*, *13*, 469–483.

Jonsen, I. D., Flemming, J. M., & Myers, R. A. (2005). Robust state–space modeling of animal movement data. *Ecology*, *86*(11), 2874–2880.

Kennedy, A. S., Zerbini, A. N., Rone, B. K., & Clapham, P. J. (2014). Individual variation in movements of satellite-tracked humpback whales megaptera novaeangliae in the eastern aleutian islands and bering sea. *Endangered Species Research*, *23*(2), 187–195.

King, A. J., & Sueur, C. (2011). Where next? group coordination and collective decision making by primates. *International journal of primatology*, *32*, 1245–1267.

Kranstauber, B., Cameron, A., Weinzerl, R., Fountain, T., Tilak, S., Wikelski, M., & Kays, R. (2011). The movebank data model for animal tracking. *Environmental Modelling & Software*, *26*(6), 834–835.

Leathwick, J., Elith, J., Francis, M., Hastie, T., & Taylor, P. (2006). Variation in demersal fish species richness in the oceans surrounding new zealand: An analysis using boosted regression trees. *Marine ecology progress series*, *321*, 267–281.

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., Pell, A. N., Deadman, P., Kratz, T., Lubchenco, J., et al. (2007). Complexity of coupled human and natural systems. *science*, *317*(5844), 1513–1516.

Loh, W.-Y. (2011). Classification and regression trees. *Wiley interdisciplinary reviews: data mining and knowledge discovery*, *1*(1), 14–23.

Long, J., Nelson, T., & Wulder, M. (2010). Regionalization of landscape pattern indices using multivariate cluster analysis. *Environmental management*, *46*, 134–142.

Long, J., & Nelson, T. A. (2012). Time geography and wildlife home range delineation. *The Journal of Wildlife Management*, *76*(2), 407–413.

Long, J., & Nelson, T. A. (2013). Measuring dynamic interaction in movement data. *Transactions in GIS*, *17*(1), 62–77.

Loraamm, R. W. (2020). Incorporating behavior into animal movement modeling: A constrained agent-based model for estimating visit probabilities in space-time prisms. *International Journal of Geographical Information Science*, *34*(8), 1607–1627.

Martin, L. J., Blossey, B., & Ellis, E. (2012). Mapping where ecologists work: Biases in the global distribution of terrestrial ecological observations. *Frontiers in Ecology and the Environment*, *10*(4), 195–201.

Miller, H. J., Dodge, S., Miller, J., & Bohrer, G. (2019). Towards an integrated science of movement: Converging research on animal movement ecology and human mobility science. *International Journal of Geographical Information Science*, *33*(5), 855–876.

Nathan, R., Getz, W. M., Revilla, E., Holyoak, M., Kadmon, R., Saltz, D., & Smouse, P. E. (2008). A movement ecology paradigm for unifying organismal movement research. *Proceedings of the National Academy of Sciences*, *105*(49), 19052–19059.

Oloo, F., & Wallentin, G. (2017). An adaptive agent-based model of homing pigeons: A genetic algorithm approach. *ISPRS International Journal of Geo-Information*, *6*(1), 27.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al. (2011). Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, *12*, 2825–2830.

Perez, L., Eun-kyeong, K., & Sengupta, R. (2018). Agent-based models and complexity science in the age of geospatial big data. *Cham: Springer Nature. doi*, *10*, 978–3.

Pérez, L., & Dragićević, S. (2011). Forestsimmpb: A swarming intelligence and agent-based modeling approach for mountain pine beetle outbreaks. *Ecological informatics*, *6*(1), 62–72.

R Core Team. (2020). R: A language and environment for statistical computing. https://cir.nii.ac.jp/crid/1370294721063650048

Semeniuk, C. A., Haider, W., Cooper, A., & Rothley, K. D. (2010). A linked model of animal ecology and human behavior for the management of wildlife tourism. *Ecological Modelling*, *221*(22), 2699–2713.

Stallknecht, D. (2007). Impediments to wildlife disease surveillance, research, and diagnostics. *Wildlife and emerging zoonotic diseases: the biology, circumstances and consequences of cross-species transmission*, 445–461.

Strand, E., Huse, G., & Giske, J. (2002). Artificial evolution of life history and behavior. *The American Naturalist*, *159*(6), 624–644.

Strandburg-Peshkin, A., Farine, D. R., Couzin, I. D., & Crofoot, M. C. (2015). Shared decision-making drives collective movement in wild baboons. *Science*, *348*(6241), 1358–1361.

Sutton, R. S., & Barto, A. G. (1999). Reinforcement learning: An introduction. *Robotica*, *17*(2), 229–235.

Tang, W., & Bennett, D. A. (2010). Agent-based modeling of animal movement: A review. *Geography Compass*, *4*(7), 682–700.

Torrens, P., Li, X., & Griffin, W. A. (2011). Building agent-based walking models by machine-learning on diverse databases of space-time trajectory samples. *Transactions in GIS*, *15*, 67–94.

Tyrrell, M. (2007). Sentient beings and wildlife resources: Inuit, beluga whales and management regimes in the canadian arctic. *Human Ecology*, *35*, 575–586.

Ward, J. A., Evans, A. J., & Malleson, N. S. (2016). Dynamic calibration of agent-based models using data assimilation. *Royal Society open science*, *3*(4), 150703.

Whoriskey, K., Auger-Méthé, M., Albertsen, C. M., Whoriskey, F. G., Binder, T. R., Krueger, C. C., & Mills Flemming, J. (2017). A hidden markov movement model for rapidly identifying behavioral states from animal tracks. *Ecology and evolution*, *7*(7), 2112–2121.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., et al. (2019). Welcome to the tidyverse. *Journal of open source software*, *4*(43), 1686.

Williams, H. J., Taylor, L. A., Benhamou, S., Bijleveld, A. I., Clay, T. A., de Grissac, S., Demšar, U., English, H. M., Franconi, N., Gómez-Laich, A., et al. (2020). Optimizing the use of biologgers for movement ecology research. *Journal of Animal Ecology*, *89*(1), 186–206.

Zhang, D., Lee, K., & Lee, I. (2019). Semantic periodic pattern mining from spatio-temporal trajectories. *Information Sciences*, *502*, 164–189.

4 Discussion

Data-driven or algorithmic approaches to informing agent-based models contribute to a broader call for GIScience methods to reduce emphasis on data authority (Sieber & Haklay, 2015). As an alternative to expert-calibrated agent-based models, I have developed and demonstrated a new data-driven calibration technique using inductive learning and classification trees. By considering bottom-up (i.e., either data-driven agent-based models or participatory agent-based models) instead of top-down (i.e., expert-calibrated agent-based models) methods to simulate movement in complex systems, agent-based movement models are more likely to be *locally* valid (Buchholtz et al., 2020; Carnap, 1995) and, potentially, nurture resilience in socioecological systems (Tyler et al., 2007). In this discussion I extend ideas introduced in chapter three related to the olive baboon (*Papio anubis*) troop agent-based model; suggest future directions for this baboon-agent model; and present participatory methods as complimentary to data-driven approaches to modelling animal movement in socioecological systems.

Methods and results discussed in the preceding chapter described an algorithmic GeoAI technique for informing an agent-based model of animal movement. Taking advantage of high temporal resolution, this novel GeoAI technique aligns with the movement ecology framework as simulations represent movement as emergent spatiotemporal phenomena based on interplay between an individual baboon's internal state, motion capacity, navigation capacity, and other, often social or environmental, external factors (Holyoak et al., 2008; Nathan et al., 2008).

This thesis was guided by the following research questions:

Can agent rules extracted from classification trees be incorporated into an agent-based simulation of an animal group? Do simulated trajectories represent their real-world counterparts? Do animal-agent and real-world animals appear to have similar space use patterns?

An additional question arose during study:

Can people embedded within study systems play an active role in developing policy evaluation tools?

4.1 Baboon Agents

Baboon-agents, the artificial baboon individuals or groups in a simulated environment, move through geographic space akin to their real-world counterparts (in chapter three, and in similar work: (Di Fiore, 2021).) In my work, individual agents were calibrated using: a) species-specific ecological knowledge to define what reasonable threshold exists for path segmentation; b) applied machine learning literature on what are acceptable parameters for classification tree building and pruning; c) the aggregate behaviour selection surfaces as defined by nodal rules of a classification tree (as described in chapter three); and d) modulating step-selection and agent-vision cone angle.

The baboon-agent model is a demonstration of an innovative GeoAI technique for informing agent-based models of animal movement. This technique - "Transferring decision boundaries onto a geographic space" - extracts decision rules from classification trees and processes, re-weights, and develops movement rationales for agents. As agents traverse simulated space, based on data-driven movement rationales, they visualise animal-agent space use. Aggregated spatial rules are referred to as a 'behaviour selection surface'. Atop this selection surface, baboon-agents move from sleeping site to set destinations. Simulated trajectories match actual observed trajectories with high fidelity for two of four days. On the days the model did not match observed trajectories, the troop did not venture to known destinations in the study area (Strandburg-Peshkin et al., 2015).

As discussed above, the purpose of this model is to showcase a new way of informing agent-based models of animal movement. As Hebblewhite and Haydon (2010) argue for clearer boundaries between geo-spatial technological advancements and insight into ecological phenomena. Consequently, we pay particular attention to this concern while developing big geospatial data approaches to modelling animal movement - a role ecologists have outlined for geographers and geographic information scientists (Williams et al., 2020).

4.1.1 Boosted-Baboons: Gradient Descent for Agent-Based Models

As the current baboon-agent model architecture is based on a single classification tree, it is amenable to ensemble tree-based techniques. That is, taking an average of multiple trees, via either random forest models or gradient boosted approaches, would not require substantial changes to the existing model architecture. Boosted Regression Trees (BRTs) are decision trees applied iteratively to find and average many rough rules, rather than operate on a single rule with limited predictive capacity

(Elith et al., 2008). BRTs are a collection of many relatively inaccurate rules to create an accurate prediction rule (Freund, Schapire, et al., 1996).

In gradient descent, at each iteration, or step-down, a new tree is selected based on some predefined loss function. For example, deviance, can represent the loss in predictive performance occurring due to a model being sub-optimal (Elith et al., 2008). Therefore, decreases in deviance signify an increase in predictive performance. At each iteration, a new tree is added with increased emphasis (or weight) on observations that were previously modelled poorly (Freund, Schapire, et al., 1996; Friedman, 2001). While the initial tree is constructed and selected based on: desired complexity; and whichever tree provides optimal performance, subsequent trees are selected based on greatest further reductions in the loss function (Elith et al., 2008). This eventual crawl towards some minima is gradient descent in action. This distinguishing characteristic of boosting is a forward iterative process: increasing emphasis on observations that were poorly modelled by the collection of trees that came before the latest additional tree. Trees continue to be added if reductions to the loss function are greater than the pre-set tolerance for convergence.

Exciting work already exists using BRTs on short-finned eel (*Anguilla australis*) distribution in New Zealand (Elith et al., 2008); identifying likely *Rodentia* reservoirs of zoonotic diseases (Han et al., 2015); and habitat modelling for animal conservation (Leathwick et al., 2006; Wintle et al., 2005). Related to the described context in chapter three (olive baboons in Mpala, Kenya), BRTs may be better better suited to extract which places are best associated with different types of movements or behaviours. Subsequently, their inclusion in the existing model architecture may improve predictive performance related to which places (or units of space and time) might serve a species best for a given type of species-specific movement. Additionally, ensemble approaches could be used to improve baboon-agent model accuracy by incorporating a wider set of internal as well as social or environmental features. Accordingly, model behaviour selection can become better defined by various ecological processes. For example, an individual might choose to sleep (a type of movement characterized by zero movement velocity, and unique internal states, like metabolism at or near the expected Basal Resting Rate), in areas that are inaccessible to predators. While it may be difficult to detect where predators are, areas that are inaccessible to predators may be defined by some combination of environmental features. Red-bellied tamarins (*Saguinus labiatus*) select their sleeping sites based on the degree of concealment a given location offers; tufted capuchin monkeys (*Cebus apella*) prefer sleeping in the leaves of Jessina palms as access for predatory cats becomes limited; and bonobos (*Pan paniscus*) build their nests high in trees, presumably to avoid predators (J. R. Anderson, 1998; Fruth & Hohmann, 1993; Goodall, 1962). Each of these could be described, as is done in the current baboon-agent model, by the relative distance a point is to environmental features; thick bush cover; Jessina palms; and tall trees can all be digitized using remote sensing products and GIS. Should enough environmental features relevant to the ecology of a given species be encoded, a broad interpretation of the region as it relates to how well a given space and time facilitates a type of movement could be produced. Such outputs would be valuable for wildife, conservation, or environmental policy.

4.1.2 Unexpected Behaviour

Baboon-agents in our model unexpectedly traversed across a shallow river point in the environment, potentially an example of *emergence* (see Figure 6 and crossing point). Such characteristics of the environment are a form of interaction between environment and individual navigation capacity (Tang & Bennett, 2010). This remarkable point of alignment between simulated and real-world trajectories may have occurred due to similarities in environmental structure in both real and simulated systems. Acknowledging Occam's razor, obvious simpler rationalisations include: issues with river digitization which may have introduced geometry errors; or step modulation (see Table 1 of agent internal logic) having enabled animal-agents to directly pass the shallow river points when stuck.

Examples of emergence in agent-based simulations appear across a variety of disciplines (Fromm, 2005). For example, segregation in cities and collective animal movements are popular examples of an emergent pattern (Bonnell et al., 2013; Bouarfa et al., 2013; Helbing, 2012; Sun & Manson, 2015). As an alternative example: Bouarfa et al. (2013) model complex air transportation behaviour and outline how their use of agent-based models and rare-event Monte Carlo simulations enable 'lever' point discovery of a complex sociotechnical system (i.e., air traffic management). Such points amplify resilience or greatly affect outcomes, yet are not planned and appear on their own in unknown ways.

Further, Janssen et al. (2019) developed methods to describe causality using graphs to visualise linkages between parameters in an effort to better contextualise emergence across systems. Batty and Torrens (2005) discussed how such information visualisation would be near impossible to observe in reality (as opposed to in simulation). Heppenstall et al. (2021) reiterated the importance of algorithmic approaches to better contextualise and communicate emergence in agent-based simulations of spatial systems.

4.2 Humans in the Loop

The rationalisation for de-emphasizing data authority in agent-based approaches to modelling animal movement is clear on multiple fronts. As eluded to in chapter three and earlier, people have inherent situated knowledge of the ecosystems they inhabit (Haraway, 2004). Magnifying this bias, animal ecology has a historic focus on ecological as opposed to socioecological systems (Martin et al., 2012). As computational models, and especially agent-based models as policy evaluation tools, inform environmental policy, peoples' collective situated knowledge of their systems can be used to validate insight from data-driven models. To counter the prevailing practice of expert-calibration, agent-based approaches must accept input from people embedded within study systems being modelled. That is, having people express their own socioecological relations using qualitative techniques may aid in developing better situated agent-based models of animal movement. Therefore participatory agent-based modelling is proposed as an innovative and complementary to data-driven, method for informing agent based models of animal movement. Further discussion related to this convergence between PGIS and ABMs follows.

4.2.1 Advancing Participatory Agent-Based Models of Animal Movement

While this thesis advanced an algorithmic approach to simulating animal movement, agent-based models can also be co-designed with communities, potentially re-orienting the purpose and outputs of participatory agent-based models to align with local objectives, values, and knowledge systems (Eitzel et al., 2020). Local or traditional ecological knowledge in tightly-coupled systems holds potential for improving computational movement analysis (Buchholtz et al., 2020). Participatory agent-based models and spatial agent-based models are common techniques for simulating systems and linking outcomes with policy interventions (Bonnell, Ghai, et al., 2016; Eitzel et al., 2020). Despite recent advancements, notably in spatial integrations for agent-based modeling (i.e., open source GIS integrations using shapely and geopandas for MESA) (Masad & Kazil, 2015); object-oriented design standards (Grimm et al., 2020); and access to geo-computational resources, participatory computational methods remain underutilised in movement research applications.

Loarie et al. (2009) show the rate at which animal movements are changing is increasing, exacerbating concern regarding climate vulnerability and ecosystem collapse. Communities in socioecological systems facing vulnerability continue to adapt using a wide range of tools and technologies (Gautam et al., 2013; Tirivangasi & Nyahunda, 2019). In some cases, having combined local and scientific information in novel ways to achieve community determined objectives (Eitzel et al., 2020; Ramanath & Gilbert, 2004; Roncoli et al., 2002; Schlingmann et al., 2021). Popular statistical techniques for modeling animal movement (e.g., resource selection methods) have improved accuracy when integrated with traditional or local ecological knowledge (Buchholtz et al., 2020). Like selection methods, ABMs are often calibrated using expert opinion. For both techniques people living within study systems can better represent their socioecological relations, enabling improved computational models of movement at, as Buchholtz et al., notes, local scales (Buchholtz et al., 2020). Such disruptive movement analysis application would support adaptiveness of socioecological systems. Established object-oriented design protocols for agent based modelling (Grimm et al., 2020); efforts towards a taxonomy of animal movement patterns (Dodge et al., 2008); and open source geocomputational simulation tools (Masad & Kazil, 2015) encourage transfer and generalization of techniques without outright disqualification of the potential for these to be adapted by Indigenous people abiding by local conceptualisations of space (Eitzel et al., 2020).

Traditional ecological knowledge, particularly in Indigenous contexts, functions well in helping communities to understand complex ecosystem traits and challenges (H. Huntington et al., 2004; H. P. Huntington, 2000; Snively & Corsiglia, 2001). Community-determined adaptations are a demonstration of essential knowledge necessary for new disruptive forms of simulation that are focused on community adaptation in response to increasing climate vulnerability. Willcock et al. (2023) discuss the importance of simulation methods' capacity to handle 'noise', highlighting the need for local information to better combat ecosystem collapse, while Ramanath and Gilbert (2004) suggest techniques for effective participatory agent-based modelling drawing on software engineering literature (Ramanath & Gilbert, 2004; Willcock et al., 2023). The adaptive capacity of socioecological systems are particularly relevant to avoid global ecosystem collapse and various related catastrophes (Altizer et al., 2007; Bradley & Altizer, 2007; Jenkins et al., 2015; Semeniuk et al., 2010). Outlined below, animal movements are unique in their centrality to being effected by and affecting both anthropogenic as well as environmental events. This centrality offers the spatiotemporal phenomena of animal movement a position a sentinel marker of rapid social and environmental change. This keystone position is fundamental to understanding system-level resilience.

Table 2: Centrality of animal movement in socioecological systems

Social components –>	**<– Animal movement –>**	**<– Environment**
Inuit hunting practices	Caribou migration	Ice phenology
Community-led tiger culling	Tiger resource selection	Changing forest resources
Saami herding practices	Reindeer resource selection	Food availability
Anishinaabe fire practices	Bison resource selection	Distribution of resources
Hunters of the Calakmul	Peccary habitat selection	Availability of water

Further, altering the power landscape underlying knowledge production can lead to more adaptive and resilient socio-ecological systems. By including people embedded within study systems into model development and calibration phases, more *locally* valid representations of animal movement and socio-ecological interaction can inform simulations (Buchholtz et al., 2020; Eitzel et al., 2020). Model outputs from such better informed representations may be more culturally sensitive, contextually relevant, locally valid, and importantly, less morally ambiguous.

4.3 Summary

This section expanded considerably into model-making aspects of agent-based simulations of animal movement, highlighting discussion points from chapter three; extending to future directions; and relating these to contemporary literature. Enabled by ever-expanding scale and resolution of movement data, our GeoAI approach enables improved agent-based modelling of a spatial systems due to inductive learning and classification tree based techniques. A gradient descent baboon-agent model could enhance model accuracy. Similarly, involving people embedded within study systems may prove to be an effective means to improve models of socioecological systems. This inclusion, is critical on multiple fronts and should be considered as part of a broader shift away from expert-calibrated simulations of social systems.

5 Conclusion

In this thesis I explored new ways of developing simulations of animal movement. Specifically, an innovative technique for informing local agent-rules using classification trees and environmental data, and participatory agent-based modelling as a disruptive application of computational movement analysis. As simulation technologies premised upon artificial object-oriented design principles (Grimm et al., 2020), agent-based models are effective tools for policy evaluation (Crooks et al., 2008; Marshall & Duthie, 2022; Tang & Bennett, 2010). This thesis demonstrates and discusses alternative means to informing such policy-oriented agent-based models of animal movement. That is, by transferring decision boundaries onto a geographic space, and by proposing the inclusion of peoples embedded in study systems.

5.1 Contribution to Geographic Information Science

Agent-based models are well suited to fill gaps between more formal, restricted models and thick description of place (Page, 2008). Building *bottom-up* simulations can be understood as capturing phenomena which emerges due to lower-level interactions; and/or as enabling a change in material conditions for people embedded within study systems who decry state policy as the largest hurdle to their adaptive capacity (Tyler et al., 2007). The baboon-agent model in chapter three demonstrated an innovative GeoAI approach to simulating animal movement. This contribution to GIScience, geosimulation, and computational movement analysis falls within and further encourages data-driven methods for spatial simulation. Part of the rationale for algorithmic approaches to agent-based modelling includes a necessary shift away from expert-calibrated simulation. An additional, and to be frank, obvious data source for non-expert calibrated models of animal movement includes people who interact or otherwise share space with study species. As mentioned above in chapter three and in discussion, people within tightly coupled socioecological systems hold important situated knowledge of ecosystem traits, services, and challenges. This discursive contribution to GIScience and geosimulation complements well with other increasingly computational participatory approaches to modelling spatial systems. Both approaches respond to calls to de-emphasize data authority in GIScience and social simulation.

References

Adam, C., & Gaudou, B. (2017). Modelling human behaviours in disasters from interviews: Application to melbourne bushfires. *Journal of Artificial Societies and Social Simulation*, *20*(3).

Adey, P., Bissell, D., Hannam, K., Merriman, P., & Sheller, M. (2014). *The routledge handbook of mobilities*. Routledge.

Ahas, R., Aasa, A., Silm, S., & Tiru, M. (2010). Daily rhythms of suburban commuters' movements in the tallinn metropolitan area: Case study with mobile positioning data. *Transportation Research Part C: Emerging Technologies*, *18*(1), 45–54.

Ahearn, S. C., Smith, J. L. D., Joshi, A. R., & Ding, J. (2001). Tigmod: An individual-based spatially explicit model for simulating tiger/human interaction in multiple use forests. *Ecological Modelling*, *140*(1-2), 81–97.

Alderton, S., Noble, J., Schaten, K., Welburn, S. C., & Atkinson, P. M. (2015). Exploiting human resource requirements to infer human movement patterns for use in modelling disease transmission systems: An example from eastern province, zambia. *PLoS One*, *10*(9), e0139505.

Altizer, S., Nunn, C. L., & Lindenfors, P. (2007). Do threatened hosts have fewer parasites? a comparative study in primates. *Journal of Animal Ecology*, *76*(2), 304–314.

Amouroux, E., Taillandier, P., & Drogoul, A. (2010). Complex environment representation in epidemiology abm: Application on h5n1 propagation. *Journal of science and technology*, 13–25.

An, L., Grimm, V., Sullivan, A., Turner Ii, B., Malleson, N., Heppenstall, A., Vincenot, C., Robinson, D., Ye, X., Liu, J., et al. (2021). Challenges, tasks, and opportunities in modeling agent-based complex systems. *Ecological Modelling*, *457*, 109685.

Anderson, J. H., Downs, J. A., Loraamm, R., & Reader, S. (2017). Agent-based simulation of muscovy duck movements using observed habitat transition and distance frequencies. *Computers, Environment and Urban Systems*, *61*, 49–55.

Anderson, J. R. (1998). Sleep, sleeping sites, and sleep-related activities: Awakening to their significance. *American Journal of Primatology*, *46*(1), 63–75.

Anderson, T., & Dragićević, S. (2015). An agent-based modeling approach to represent infestation dynamics of the emerald ash borer beetle. *Ecological Informatics*, *30*, 97–109.

Ardestani, B. M., O'Sullivan, D., & Davis, P. (2018). A multi-scaled agent-based model of residential segregation applied to a real metropolitan area. *Computers, Environment and Urban Systems*, *69*, 1–16.

Aswani, S., & Lauer, M. (2006). Incorporating fishermen's local knowledge and behavior into geographical information systems (gis) for designing marine protected areas in oceania. *Human organization*, *65*(1), 81–102.

Avolio, M. V., Errera, A., Lupiano, V., Mazzanti, P., & Di Gregorio, S. (2010). Development and calibration of a preliminary cellular automata model for snow avalanches. *Cellular Automata: 9th International Conference on Cellular Automata for Research and Industry, ACRI 2010, Ascoli Piceno, Italy, September 21-24, 2010. Proceedings 9*, 83–94.

Avolio, M. V., Errera, A., Lupiano, V., Mazzanti, P., & Di Gregorio, S. (2017). Valanca: A cellular automata model for simulating snow avalanches. *Journal of Cellular Automata*, *12*(5).

Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., & Nagel, K. (2009). Matsim-t: Architecture and simulation times. In *Multi-agent systems for traffic and transportation engineering* (pp. 57–78). IGI Global.

Barberousse, A., & Ludwig, P. (2008). Models as fictions. In *Fictions in science* (pp. 64–82). Routledge.

Barbosa, H., Barthelemy, M., Ghoshal, G., James, C. R., Lenormand, M., Louail, T., Menezes, R., Ramasco, J. J., Simini, F., & Tomasini, M. (2018). Human mobility: Models and applications. *Physics Reports*, *734*, 1–74.

Barkley, A. N., Broell, F., Pettitt-Wade, H., Watanabe, Y. Y., Marcoux, M., & Hussey, N. E. (2020). A framework to estimate the likelihood of species interactions and behavioural responses using animal-borne acoustic telemetry transceivers and accelerometers. *Journal of Animal Ecology*, *89*(1), 146–160.

Basille, M., Urbano, F., Racine, P., Capecchi, V., & Cagnacci, F. (2014). Tracking animals in a dynamic environment: Remote sensing image time series. *Spatial Database for GPS Wildlife Tracking Data: A Practical Guide to Creating a Data Management System with PostgreSQL/PostGIS and R*, 95–114.

Batty, M. (2001). Agent-based pedestrian modeling.

Batty, M., & Torrens, P. M. (2005). Modelling and prediction in a complex world. *Futures*, *37*(7), 745–766.

Bedini, E. (2017). The use of hyperspectral remote sensing for mineral exploration: A review. *Journal of Hyperspectral Remote Sensing*, *7*(4), 189–211.

Bennett, D. A., & Tang, W. (2006). Modelling adaptive, spatially aware, and mobile agents: Elk migration in yellowstone. *International Journal of Geographical Information Science*, *20*(9), 1039–1066.

Bernardes, S., Eury, A. H., Presotto, A., Madden, M., Jordan, T., Fragaszy, D. M., Izar, P., & Tavares-Rocha, Y. (2011). An agent based modeling approach for representing capuchin (sapajus spp.) behavior in brazil. *Proceedings Of The Annual Conference-American Society For Photogrammetry AND Remote Sensing*, 41–47.

Bernardini, G., D'Orazio, M., Quagliarini, E., & Spalazzi, L. (2014). An agent-based model for earthquake pedestrians' evacuation simulation in urban scenarios. *Transportation Research Procedia*, *2*, 255–263.

Bian, L. (2013). Spatial approaches to modeling dispersion of communicable diseases–a review. *Transactions in GIS*, *17*(1), 1–17.

Bickel, P. J., Ritov, Y., & Stoker, T. M. (2006). Tailor-made tests for goodness of fit to semiparametric hypotheses. *The Annals of Statistics*, *34*(2), 721–741. https://doi.org/10.1214/009053606000000137

Bishop, I. D., & Gimblett, H. (2000). Management of recreational areas: Gis, autonomous agents, and virtual reality. *Environment and Planning B: Planning and Design*, *27*(3), 423–435.

Boldrini, C., & Passarella, A. (2010). Hcmm: Modelling spatial and temporal properties of human mobility driven by users' social relationships. *Computer Communications*, *33*(9), 1056–1074.

Bonnell, T. R., Campennı´, M., Chapman, C. A., Gogarten, J. F., Reyna-Hurtado, R. A., Teichroeb, J. A., Wasserman, M. D., & Sengupta, R. (2013). Emergent group level navigation: An agent-based evaluation of movement patterns in a folivorous primate. *PloS one*, *8*(10), e78264.

Bonnell, T. R., Chapman, C. A., & Sengupta, R. (2016). Interaction between scale and scheduling choices in simulations of spatial agents. *International Journal of Geographical Information Science*, *30*(10), 2075–2088.

Bonnell, T. R., Ghai, R. R., Goldberg, T. L., Sengupta, R., & Chapman, C. A. (2016). Spatial patterns of persistence for environmentally transmitted parasites: Effects of regional climate and local landscape. *Ecological Modelling*, *338*, 78–89.

Bonnell, T. R., Sengupta, R. R., Chapman, C. A., & Goldberg, T. L. (2010). An agent-based model of red colobus resources and disease dynamics implicates key resource sites as hot spots of disease transmission. *Ecological Modelling*, *221*(20), 2491–2500.

Bouarfa, S., Blom, H. A., Curran, R., & Everdij, M. H. (2013). Agent-based modeling and simulation of emergent behavior in air transportation. *Complex Adaptive Systems Modeling*, *1*, 1–26.

Braae, U. C., Devleesschauwer, B., Gabriël, S., Dorny, P., Speybroeck, N., Magnussen, P., Torgerson, P., & Johansen, M. V. (2016). Cystisim–an agent-based model for taenia solium transmission and control. *PLoS neglected tropical diseases*, *10*(12), e0005184.

Bradley, C. A., & Altizer, S. (2007). Urbanization and the ecology of wildlife diseases. *Trends in ecology & evolution*, *22*(2), 95–102.

Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). *Statistical science*, *16*(3), 199–231.

Bryson, J. J., Ando, Y., & Lehmann, H. (2007). Agent-based modelling as scientific method: A case study analysing primate social behaviour. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1485), 1685–1699.

Buchholtz, E., Fitzgerald, L., Songhurst, A., McCulloch, G., & Stronza, A. (2020). Experts and elephants: Local ecological knowledge predicts landscape use for a species involved in human-wildlife conflict. *Ecology and Society*, *25*(4).

Calenge, C. (2006). The package "adehabitat" for the r software: A tool for the analysis of space and habitat use by animals.

Carnap, R. (1995). *An introduction to the philosophy of science* (M. Gardner, Ed.). Courier Corporation.

Carter, N. H., Gurung, B., Viña, A., Campa III, H., Karki, J. B., & Liu, J. (2013). Assessing spatiotemporal changes in tiger habitat across different land management regimes. *Ecosphere*, *4*(10), 1–19.

Cenek, M., & Franklin, M. (2017). An adaptable agent-based model for guiding multi-species pacific salmon fisheries management within a ses framework. *Ecological Modelling*, *360*, 132–149.

Chapman, C. A., Chapman, L. J., & Gillespie, T. R. (2002). Scale issues in the study of primate foraging: Red colobus of kibale national park. *American Journal of Physical Anthropology: The Official Publication of the American Association of Physical Anthropologists*, *117*(4), 349–363.

Chapman, C. A., & Reyna-Hurtado, R. (2019). Why movement ecology matters. *Movement Ecology of Neotropical Forest Mammals: Focus on Social Animals*, 1–3.

Chaudhuri, G., & Clarke, K. C. (2014). Temporal accuracy in urban growth forecasting: A study using the sleuth model. *Transactions in GIS*, *18*(2), 302–320.

Chen, X. (2008). Microsimulation of hurricane evacuation strategies of galveston island. *The Professional Geographer*, *60*(2), 160–173.

Chen, X., Meaker, J. W., & Zhan, F. B. (2006). Agent-based modeling and analysis of hurricane evacuation procedures for the florida keys. *Natural Hazards*, *38*, 321–338.

Chun, J., Psarras, S., Koutsolampros, P., et al. (2019). Agent based simulation for'choice of seats': A study on the human space usage pattern.

Cioffi-Revilla, C. (2016). Socio-ecological systems. In *Handbook of science and technology convergence* (pp. 669–689). Springer. https://doi.org/10.1007/978-3-319-07052-0_76

Clarke-Lauer, M., & Clarke, K. C. (2011). Evolving simulation modeling: Calibrating sleuth using a genetic algorithm. *Proceedings of the 11th International Conference on GeoComputation, London, UK*, *2022*, 20–22.

Corbett, J. (2009). Good practices in participatory mapping: A review prepared for the international fund for agricultural development (ifad).

Cornacchia, G., Rossetti, G., & Pappalardo, L. (2020). Modelling human mobility considering spatial, temporal and social dimensions. *arXiv preprint arXiv:2007.02371*.

Crooks, A. (2010). Constructing and implementing an agent-based model of residential segregation through vector gis. *International Journal of Geographical Information Science*, *24*(5), 661–675.

Crooks, A., Castle, C., & Batty, M. (2008). Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems*, *32*(6), 417–430.

Crooks, A., Croitoru, A., Lu, X., Wise, S., Irvine, J. M., & Stefanidis, A. (2015). Walk this way: Improving pedestrian agent-based models through scene activity analysis. *ISPRS International Journal of Geo-Information*, *4*(3), 1627–1656.

Crooks, A., & Hailegiorgis, A. B. (2014). An agent-based modeling approach applied to the spread of cholera. *Environmental Modelling & Software*, *62*, 164–177.

Crooks, A., Patel, A., & Wise, S. (2014). Multi-agent systems for urban planning. In *Technologies for urban and spatial planning: Virtual cities and territories* (pp. 29–56). IGI Global.

Crooks, A., & Wise, S. (2013). Gis and agent-based models for humanitarian assistance. *Computers, Environment and Urban Systems*, *41*, 100–111.

Crowley, M. A., Cardille, J. A., White, J. C., & Wulder, M. A. (2019). Multi-sensor, multi-scale, bayesian data synthesis for mapping within-year wildfire progression. *Remote sensing letters*, *10*(3), 302–311.

Currie, C. S., Fowler, J. W., Kotiadis, K., Monks, T., Onggo, B. S., Robertson, D. A., & Tako, A. A. (2020). How simulation modelling can help reduce the impact of covid-19. *Journal of Simulation*, *14*(2), 83–97.

Dai, E., Ma, L., Yang, W., Wang, Y., Yin, L., & Tong, M. (2020). Agent-based model of land system: Theory, application and modelling framework. *Journal of Geographical Sciences*, *30*, 1555–1570.

Dardashti, R., Thébault, K. P., & Winsberg, E. (2017). Confirmation via analogue simulation: What dumb holes could tell us about gravity. *The British Journal for the Philosophy of Science*.

DeAngelis, D. L., & Diaz, S. G. (2019). Decision-making in agent-based modeling: A current review and future prospectus. *Frontiers in Ecology and Evolution*, *6*, 237.

del Mar Delgado, M., Miranda, M., Alvarez, S. J., Gurarie, E., Fagan, W. F., Penteriani, V., di Virgilio, A., & Morales, J. M. (2018). The importance of individual variation in the dynamics of animal collective movements. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1746), 20170008.

Demsar, U., Long, J., & Sila-Nowicka, K. (2020). Integrated science of movement. *Journal of Spatial Information Science*, *21*, 25–31. https://doi.org/10.5311/JOSIS.2020.21.721

Demšar, U. (2022). Investigating geomagnetic bird navigation: 4d data fusion of co-located gps and magnetometer data.

Demšar, U., Buchin, K., Cagnacci, F., Safi, K., Speckmann, B., Van de Weghe, N., Weiskopf, D., & Weibel, R. (2015). Analysis and visualisation of movement: An interdisciplinary review. *Movement ecology*, *3*(1), 1–24.

Deygout, C., Gault, A., Sarrazin, F., & Bessa-Gomes, C. (2009). Modeling the impact of feeding stations on vulture scavenging service efficiency. *Ecological modelling*, *220*(15), 1826–1835.

Di Fiore, A. (2021). 14 the promise of spatially explicit agent-based models for primatology research. *Spatial Analysis in Field Primatology: Applying GIS at Varying Scales*, 280.

Diallo, A. O., Gloriot, T., & Manout, O. (2023). Agent-based simulation of shared bikes and e-scooters: The case of lyon. *Procedia Computer Science*, *220*, 364–371. https://doi.org/10.1016/j.procs.2023.03.047

Diaz, S. G., DeAngelis, D. L., Gaines, M. S., Purdon, A., Mole, M. A., & van Aarde, R. J. (2021). Development and validation of a spatially-explicit agent-based model for space utilization by african savanna elephants (loxodonta africana) based on determinants of movement. *Ecological modelling*, *447*, 109499.

Dijkstra, J., Timmermans, H. J., & Jessurun, A. (2001). A multi-agent cellular automata system for visualising simulated pedestrian activity. *Theory and Practical Issues on Cellular Automata: Proceedings of the Fourth International Conference on Cellular Automata for Research and Industry, Karlsruhe, 4-6 October 2000*, 29–36.

Dion, E., VanSchalkwyk, L., & Lambin, E. F. (2011). The landscape epidemiology of foot-and-mouth disease in south africa: A spatially explicit multi-agent simulation. *Ecological Modelling*, *222*(13), 2059–2072.

Diuana, J. C., De Farias, O. L. M., & Bernardo Filho, O. (2006). Simulation of the dissemination of slums in cities through reactive agents. *2006 International Conference on Computational Inteligence for Modelling Control and Automation and International Conference on Intelligent Agents Web Technologies and International Commerce (CIMCA'06)*, 132–132.

Diuana, J. C., de Farias, O. L. M., et al. (2007). Using reactive agents to mimic the dissemination of slums in cities. *Seventh International Conference on Intelligent Systems Design and Applications (ISDA 2007)*, 907–912.

Dodge, S., Bohrer, G., Weinzierl, R., Davidson, S. C., Kays, R., Douglas, D., Cruz, S., Han, J., Brandes, D., & Wikelski, M. (2013). The environmental-data automated track annotation (env-data) system: Linking animal tracks with environmental data. *Movement ecology*, *1*(1), 1–14.

Dodge, S., Gao, S., Tomko, M., & Weibel, R. (2020). Progress in computational movement analysis–towards movement data science.

Dodge, S., Weibel, R., Ahearn, S. C., Buchin, M., & Miller, J. A. (2016). Analysis of movement data. *International Journal of Geographical Information Science*, *30*(5), 825–834.

Dodge, S., Weibel, R., & Lautenschütz, A.-K. (2008). Towards a taxonomy of movement patterns. *Information visualization*, *7*(3-4), 240–252.

Dozier, J., & Painter, T. H. (2004). Multispectral and hyperspectral remote sensing of alpine snow properties. *Annu. Rev. Earth Planet. Sci.*, *32*, 465–494.

Dragićević, S. (2010). Modeling the dynamics of complex spatial systems using gis, cellular automata and fuzzy sets applied to invasive plant species propagation. *Geography Compass*, *4*(6), 599–615.

Edelhoff, H., Signer, J., & Balkenhol, N. (2016). Path segmentation for beginners: An overview of current methods for detecting changes in animal movement patterns. *Movement ecology*, *4*(1), 1–21.

Eitzel, M., Solera, J., Wilson, K., Neves, K., Fisher, A., Veski, A., Omoju, O., Mawere Ndlovu, A., & Mhike Hove, E. (2020). Indigenous climate adaptation sovereignty in a zimbabwean agro-pastoral system: Exploring definitions of sustainability success using a participatory agent-based model. *Ecology and Society*, *25*(4).

Elith, J., H. Graham, C., P. Anderson, R., Dudı´k, M., Ferrier, S., Guisan, A., J. Hijmans, R., Huettmann, F., R. Leathwick, J., Lehmann, A., et al. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, *29*(2), 129–151.

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of animal ecology*, *77*(4), 802–813.

Entwisle, B., Williams, N. E., Verdery, A. M., Rindfuss, R. R., Walsh, S. J., Malanson, G. P., Mucha, P. J., Frizzelle, B. G., McDaniel, P. M., Yao, X., et al. (2016). Climate shocks and migration: An agent-based modeling approach. *Population and environment*, *38*, 47–71.

Estrada, L. E. P., Groen, D., & Ramirez-Marquez, J. E. (2017). A serious video game to support decision making on refugee aid deployment policy. *Procedia Computer Science*, *108*, 205–214.

Farquharson, A. (1912). Aristotle, de motu animalium. de incessu animalium. *The Works of Aristotle translated into English*, *5*.

Farris, Z. J., Gerber, B. D., Valenta, K., Rafaliarison, R., Razafimahaimodison, J. C., Larney, E., Rajaonarivelo, T., Randriana, Z., Wright, P. C., & Chapman, C. A. (2017). Threats to a rainforest carnivore community: A multi-year assessment of occupancy and co-occurrence in madagascar. *Biological Conservation*, *210*, 116–124.

Filatova, T., Verburg, P. H., Parker, D. C., & Stannard, C. A. (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental modelling & software*, *45*, 1–7.

Fiore, S., Bakhouya, M., & Smari, W. W. (2018). On the road to exascale: Advances in high performance computing and simulations—an overview and editorial.

Fitterer, J. L., Nelson, T. A., Coops, N. C., Wulder, M. A., & Mahony, N. A. (2013). Exploring the ecological processes driving geographical patterns of breeding bird richness in british columbia, canada. *Ecological Applications*, *23*(4), 888–903.

Florax, R. J., & De Graaff, T. (2004). The performance of diagnostic tests for spatial dependence in linear regression models: A meta-analysis of simulation studies. In *Advances in spatial econometrics: Methodology, tools and applications* (pp. 29–65). Springer.

Freund, Y., Schapire, R. E., et al. (1996). Experiments with a new boosting algorithm. *icml*, *96*, 148–156.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of statistics*, 1189–1232.

Fromm, J. (2005). Types and forms of emergence. *arXiv preprint nlin/0506028*.

Fruth, B., & Hohmann, G. (1993). Ecological and behavioral aspects of nest building in wild bonobos (pan paniscus). *Ethology*, *94*(2), 113–126.

Fuentes, S., Gonzalez Viejo, C., Tongson, E., Lipovetzky, N., & Dunshea, F. R. (2021). Biometric physiological responses from dairy cows measured by visible remote sensing are good predictors of milk productivity and quality through artificial intelligence. *Sensors*, *21*(20), 6844.

Galland, S., Ansar-Ul-Haque Yasar, L. K., Knapen, L., Gaud, N., Bellemans, T., & Janssens, D. (2014). Simulation of carpooling agents with the janus platform. *J. Ubiquitous Syst. Pervasive Networks*, *5*(2), 9–15.

Galland, S., Knapen, L., Gaud, N., Janssens, D., Lamotte, O., Koukam, A., Wets, G., et al. (2014). Multi-agent simulation of individual mobility behavior in carpooling. *Transportation Research Part C: Emerging Technologies*, *45*, 83–98.

García-Marmolejo, G., Chapa-Vargas, L., Weber, M., & Huber-Sannwald, E. (2015). Landscape composition influences abundance patterns and habitat use of three ungulate species in fragmented secondary deciduous tropical forests, mexico. *Global ecology and conservation*, *3*, 744–755.

Gaudreau, J., Perez, L., & Drapeau, P. (2016). Borealfiresim: A gis-based cellular automata model of wildfires for the boreal forest of quebec in a climate change paradigm. *Ecological Informatics*, *32*, 12–27.

Gautam, M. R., Chief, K., & Smith Jr, W. J. (2013). Climate change in arid lands and native american socioeconomic vulnerability: The case of the pyramid lake paiute tribe. In *Climate change and indigenous peoples in the united states: Impacts, experiences and actions* (pp. 77–91). Springer.

Ghiyamat, A., & Shafri, H. Z. (2010). A review on hyperspectral remote sensing for homogeneous and heterogeneous forest biodiversity assessment. *International Journal of Remote Sensing*, *31*(7), 1837–1856.

Giuggioli, L., Potts, J. R., & Harris, S. (2011). Animal interactions and the emergence of territoriality. *PLoS Computational Biology*, *7*(3), e1002008.

Goodall, J. M. (1962). Nest building behavior in the free ranging chimpanzee. *Annals of the New York Academy of Sciences*, *102*(2), 455–467.

Grim, P., Rosenberger, R., Rosenfeld, A., Anderson, B., & Eason, R. E. (2013). How simulations fail. *Synthese*, *190*, 2367–2390.

Grimm, V., Railsback, S. F., Vincenot, C. E., Berger, U., Gallagher, C., DeAngelis, D. L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., et al. (2020). The odd protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism. *Journal of Artificial Societies and Social Simulation*, *23*(2).

Grosman, P. D., Jaeger, J. A., Biron, P. M., Dussault, C., & Ouellet, J.-P. (2009). Reducing moose–vehicle collisions through salt pool removal and displacement: An agent-based modeling approach. *Ecology and Society*, *14*(2).

Gudmundsson, J., Laube, P., & Wolle, T. (2008). Movement patterns in spatio-temporal data. *Encyclopedia of GIS*, *726*, 732.

Gudmundsson, J., Laube, P., & Wolle, T. (2012). Computational movement analysis. *Springer handbook of geographic information*, 423–438.

Guo, C., Buchmann, C. M., & Schwarz, N. (2019). Linking urban sprawl and income segregation–findings from a stylized agent-based model. *Environment and Planning B: Urban analytics and city science*, *46*(3), 469–489.

Hadjieleftheriou, M., Kollios, G., Tsotras, V. J., & Gunopulos, D. (2002). Efficient indexing of spatiotemporal objects. *International conference on extending database technology*, 251–268.

Haklay, M., O'Sullivan, D., Thurstain-Goodwin, M., & Schelhorn, T. (2001). "so go downtown": Simulating pedestrian movement in town centres. *Environment and planning B: Planning and design*, *28*(3), 343–359.

Han, B. A., Schmidt, J. P., Bowden, S. E., & Drake, J. M. (2015). Rodent reservoirs of future zoonotic diseases. *Proceedings of the National Academy of Sciences*, *112*(22), 7039–7044.

Haraway, D. (2004). Situated knowledges: The science question in feminism and the privilege of partial perspective. *Turning points in qualitative research: Tying knots in a handkerchief*, *2*, 21.

Hartmann, S. (1996). The world as a process: Simulations in the natural and social sciences. In *Modelling and simulation in the social sciences from the philosophy of science point of view* (pp. 77–100). Springer.

Hassani-Mahmooei, B., & Parris, B. W. (2012). Climate change and internal migration patterns in bangladesh: An agent-based model. *Environment and Development Economics*, *17*(6), 763–780.

Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (Vol. 2). Springer.

Hastings, A. (2001). Transient dynamics and persistence of ecological systems. *Ecology Letters*, *4*(3), 215–220.

Havens, K. J., & Sharp, E. J. (2015). *Thermal imaging techniques to survey and monitor animals in the wild: A methodology*. Academic Press.

Hebblewhite, M., & Haydon, D. T. (2010). Distinguishing technology from biology: A critical review of the use of gps telemetry data in ecology. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1550), 2303–2312.

Hebblewhite, M., & Merrill, E. (2008). Modelling wildlife–human relationships for social species with mixed-effects resource selection models. *Journal of applied ecology*, *45*(3), 834–844.

Helbing, D. (2012). *Social self-organization: Agent-based simulations and experiments to study emergent social behavior*. Springer.

Heppenstall, A., Crooks, A., Malleson, N., Manley, E., Ge, J., & Batty, M. (2021). Future developments in geographical agent-based models: Challenges and opportunities. *Geographical Analysis*, *53*(1), 76–91.

Heppenstall, A., Polhill, J. G., Batty, M., Hare, M., Salt, D., & Milton, R. (2023). Exascale Agent-Based Modelling for Policy Evaluation in Real-Time (ExAMPLER). In R. Beecham, J. Long, D. Smith, Q. Zhao, & S. Wise (Eds.), *12th international conference on geographic information science (giscience 2023)* (38:1–38:5). Schloss Dagstuhl – Leibniz-Zentrum für Informatik. https://doi.org/10.4230/LIPIcs.GIScience.2023.38

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Hölscher, C., Büchner, S., & Strube, G. (2013). Multi-floor buildings and human wayfinding cognition. *Behavioral & Brain Sciences*, *36*(5).

Holyoak, M., Casagrandi, R., Nathan, R., Revilla, E., & Spiegel, O. (2008). Trends and missing parts in the study of movement ecology. *Proceedings of the National Academy of Sciences*, *105*(49), 19060–19065.

Hua, L., Tang, L., Cui, S., & Yin, K. (2014). Simulating urban growth using the sleuth model in a coastal peri-urban district in china. *Sustainability*, *6*(6), 3899–3914.

Huang, Q., Parker, D. C., Filatova, T., & Sun, S. (2014). A review of urban residential choice models using agent-based modeling. *Environment and Planning B: Planning and Design*, *41*(4), 661–689.

Huang, Y., Guo, Z., Chu, H., & Sengupta, R. (2023). Evacuation simulation implemented by abm-bim of unity in students' dormitory based on delay time. *ISPRS International Journal of Geo-Information*, *12*(4), 160.

Huggins, E. M., & Schultz, E. A. (1967). San francisco bay in a warehouse.

Hughey, L. F., Hein, A. M., Strandburg-Peshkin, A., & Jensen, F. H. (2018). Challenges and solutions for studying collective animal behaviour in the wild. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1746), 20170005.

Hui-Hui, F., Hui-Ping, L., & Ying, L. (2012). Scenario prediction and analysis of urban growth using sleuth model. *Pedosphere*, *22*(2), 206–216.

Humphreys, P. (2004). *Extending ourselves: Computational science, empiricism, and scientific method*. Oxford University Press.

Humphreys, P. (2009). The philosophical novelty of computer simulation methods. *Synthese*, *169*, 615–626.

Huntington, H., Callaghan, T., Fox, S., & Krupnik, I. (2004). Matching traditional and scientific observations to detect environmental change: A discussion on arctic terrestrial ecosystems. *AMBIO: A Journal of the Human Environment*, *33*(sp13), 18–23.

Huntington, H. P. (2000). Using traditional ecological knowledge in science: Methods and applications. *Ecological applications*, *10*(5), 1270–1274.

Hussain, I., Knapen, J., Khan, M. A., Bellemans, T., Janssens, D., & Wets, G. (2015). Agent-based negotiation model for long-term carpooling: A flexible mechanism for trip departure times. *Urban Transport XXI*, *146*, 461.

Hussain, I., Knapen, L., Galland, S., Bellemans, T., Janssens, D., Wets, G., et al. (2016). Organizational-based model and agent-based simulation for long-term carpooling. *Future Generation Computer Systems*, *64*, 125–139.

Imron, M. A., Herzog, S., & Berger, U. (2011). The influence of agroforestry and other land-use types on the persistence of a sumatran tiger (panthera tigris sumatrae) population: An individual-based model approach. *Environmental management*, *48*, 276–288.

Isaacman, S., Becker, R., Cáceres, R., Martonosi, M., Rowland, J., Varshavsky, A., & Willinger, W. (2012). Human mobility modeling at metropolitan scales. *Proceedings of the 10th international conference on Mobile systems, applications, and services*, 239–252.

Iyer, A., Benitez-Paez, F., Brum-Bastos, V., Beggan, C. D., Demšar, U., & Long, J. (2022). Spatial-temporal interpolation of satellite geomagnetic data to study long-distance animal migration. *Ecological Informatics*, *72*, 101888.

Jackson, J., Forest, B., & Sengupta, R. (2008). Agent-based simulation of urban residential dynamics and land rent change in a gentrifying area of boston. *Transactions in GIS*, *12*(4), 475–491.

Janssen, S., Sharpanskykh, A., Curran, R., & Langendoen, K. (2019). Using causal discovery to analyze emergence in agent-based models. *Simulation Modelling Practice and Theory*, *96*, 101940.

Jantz, C. A., Goetz, S. J., Donato, D., & Claggett, P. (2010). Designing and implementing a regional urban modeling system using the sleuth cellular urban model. *Computers, Environment and Urban Systems*, *34*(1), 1–16.

Jenkins, E. J., Simon, A., Bachand, N., & Stephen, C. (2015). Wildlife parasites in a one health world. *Trends in Parasitology*, *31*(5), 174–180.

Jonsen, I. D., Flemming, J. M., & Myers, R. A. (2005). Robust state–space modeling of animal movement data. *Ecology*, *86*(11), 2874–2880.

Joo, R., Boone, M. E., Clay, T. A., Patrick, S. C., Clusella-Trullas, S., & Basille, M. (2020). Navigating through the r packages for movement. *Journal of Animal Ecology*, *89*(1), 248–267.

Kanagaraj, R., Wiegand, T., Kramer-Schadt, S., & Goyal, S. P. (2013). Using individual-based movement models to assess inter-patch connectivity for large carnivores in fragmented landscapes. *Biological conservation*, *167*, 298–309.

Kar, B., & Hodgson, M. E. (2008). A gis-based model to determine site suitability of emergency evacuation shelters. *Transactions in GIS*, *12*(2), 227–248.

Katzner, T. E., & Arlettaz, R. (2020). Evaluating contributions of recent tracking-based animal movement ecology to conservation management. *Frontiers in Ecology and Evolution*, *7*, 519.

Kays, R., Crofoot, M. C., Jetz, W., & Wikelski, M. (2015). Terrestrial animal tracking as an eye on life and planet. *Science*, *348*(6240), aaa2478.

Kays, R., Davidson, S. C., Berger, M., Bohrer, G., Fiedler, W., Flack, A., Hirt, J., Hahn, C., Gauggel, D., Russell, B., et al. (2022). The movebank system for studying global animal movement and demography. *Methods in Ecology and Evolution*, *13*(2), 419–431.

Kays, R., Sheppard, J., Mclean, K., Welch, C., Paunescu, C., Wang, V., Kravit, G., & Crofoot, M. (2019). Hot monkey, cold reality: Surveying rainforest canopy mammals using drone-mounted thermal infrared sensors. *International journal of remote sensing*, *40*(2), 407–419.

Keßler, C., & McKenzie, G. (2018). A geoprivacy manifesto. *Transactions in GIS*, *22*(1), 3–19.

Kim, K., Kaviari, F., Pant, P., & Yamashita, E. (2022). An agent-based model of short-notice tsunami evacuation in waikiki, hawaii. *Transportation Research Part D: Transport and Environment*, *105*, 103239. https://doi.org/10.1016/j.trd.2022.103239

King, A. J., & Sueur, C. (2011). Where next? group coordination and collective decision making by primates. *International journal of primatology*, *32*, 1245–1267.

Klemas, V. (2010). Tracking oil slicks and predicting their trajectories using remote sensors and models: Case studies of the sea princess and deepwater horizon oil spills. *Journal of Coastal Research*, *26*(5), 789–797.

Kniveton, D., Smith, C., & Wood, S. (2011). Agent-based model simulations of future changes in migration flows for burkina faso. *Global Environmental Change*, *21*, S34–S40.

Koch, A. (2014). The individual agent makes a difference in segregation simulation. *Social Simulation Conference*.

Kranstauber, B., Cameron, A., Weinzerl, R., Fountain, T., Tilak, S., Wikelski, M., & Kays, R. (2011). The movebank data model for animal tracking. *Environmental Modelling & Software*, *26*(6), 834–835.

Kwan, M.-P. (2004). Gis methods in time-geographic research: Geocomputation and geovisualization of human activity patterns. *Geografiska Annaler: Series B, Human Geography*, *86*(4), 267–280.

Lai, T., Dragićević, S., & Schmidt, M. (2013). Integration of multicriteria evaluation and cellular automata methods for landslide simulation modelling. *Geomatics, Natural Hazards and Risk*, *4*(4), 355–375.

Laperriere, V., Badariotti, D., Banos, A., & Mueller, J.-P. (2009). Structural validation of an individual-based model for plague epidemics simulation. *Ecological Complexity*, *6*(2), 102–112.

Laube, P. (2014). *Computational movement analysis*. Springer.

Laube, P. (2015). The low hanging fruit is gone: Achievements and challenges of computational movement analysis. *SIGSPATIAL Special*, *7*(1), 3–10.

Le, Q. B., Park, S. J., Vlek, P. L., & Cremers, A. B. (2008). Land-use dynamic simulator (ludas): A multi-agent system model for simulating spatio-temporal dynamics of coupled human–landscape system. i. structure and theoretical specification. *Ecological Informatics*, *3*(2), 135–153.

Leathwick, J., Elith, J., Francis, M., Hastie, T., & Taylor, P. (2006). Variation in demersal fish species richness in the oceans surrounding new zealand: An analysis using boosted regression trees. *Marine ecology progress series*, *321*, 267–281.

Li, W., Wang, S., Zhang, X., Jia, Q., & Tian, Y. (2020). Understanding intra-urban human mobility through an exploratory spatiotemporal analysis of bike-sharing trajectories. *International Journal of Geographical Information Science*, *34*(12), 2451–2474.

Liang, W., Lam, N. S.-N., Qin, X., & Ju, W. (2015). A two-level agent-based model for hurricane evacuation in new orleans. *Journal of Homeland Security and Emergency Management*, *12*(2), 407–435.

Liang, Y., & Liu, L. (2014). Modeling urban growth in the middle basin of the heihe river, northwest china. *Landscape ecology*, *29*, 1725–1739.

Lichter, M., Grinberger, A. Y., & Felsenstein, D. (2015). Simulating and communicating outcomes in disaster management situations. *ISPRS International Journal of Geo-Information*, *4*(4), 1827–1847.

Lin, Y., Fedchenia, I., LaBarre, B., & Tomastik, R. (2010). Agent-based simulation of evacuation: An office building case study. *Pedestrian and evacuation dynamics 2008*, 347–357.

Liu, C., & O'Sullivan, D. (2016). An abstract model of gentrification as a spatially contagious succession process. *Computers, Environment and Urban Systems*, *59*, 1–10.

Liu, J., & Ashton, P. S. (1998). Formosaic: An individual-based spatially explicit model for simulating forest dynamics in landscape mosaics. *Ecological modelling*, *106*(2-3), 177–200.

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., Pell, A. N., Deadman, P., Kratz, T., Lubchenco, J., et al. (2007). Complexity of coupled human and natural systems. *science*, *317*(5844), 1513–1516.

Loarie, S. R., Duffy, P. B., Hamilton, H., Asner, G. P., Field, C. B., & Ackerly, D. D. (2009). The velocity of climate change. *Nature*, *462*(7276), 1052–1055.

Long, J., & Nelson, T. A. (2012). Time geography and wildlife home range delineation. *The Journal of Wildlife Management*, *76*(2), 407–413.

Long, J., & Nelson, T. A. (2013). A review of quantitative methods for movement data. *International Journal of Geographical Information Science*, *27*(2), 292–318.

Long, J., Weibel, R., Dodge, S., & Laube, P. (2018). Moving ahead with computational movement analysis.

Loraamm, R. W. (2020). Incorporating behavior into animal movement modeling: A constrained agent-based model for estimating visit probabilities in space-time prisms. *International Journal of Geographical Information Science*, *34*(8), 1607–1627.

Lowerre-Barbieri, S. K., Kays, R., Thorson, J. T., & Wikelski, M. (2019). The ocean's movescape: Fisheries management in the bio-logging decade (2018–2028). *ICES Journal of Marine Science*, *76*(2), 477–488.

Mahiny, A. S., & Clarke, K. C. (2012). Guiding sleuth land-use/land-cover change modeling using multicriteria evaluation: Towards dynamic sustainable land-use planning. *Environment and planning B: planning and design*, *39*(5), 925–944.

Manson, S., An, L., Clarke, K. C., Heppenstall, A., Koch, J., Krzyzanowski, B., Morgan, F., O'Sullivan, D., Runck, B. C., Shook, E., et al. (2020). Methodological issues of spatial agent-based models. *Journal of Artificial Societies and Social Simulation*, *23*(1).

Manson, S. M. (2007). Challenges in evaluating models of geographic complexity. *Environment and Planning B: Planning and Design*, *34*(2), 245–260.

Mao, L., & Bian, L. (2010). Spatial–temporal transmission of influenza and its health risks in an urbanized area. *Computers, environment and urban systems*, *34*(3), 204–215.

Marshall, B. M., & Duthie, A. B. (2022). Abmanimalmovement: An r package for simulating animal movement using an agent-based model. *F1000Research*, *11*, 1182.

Martin, L. J., Blossey, B., & Ellis, E. (2012). Mapping where ecologists work: Biases in the global distribution of terrestrial ecological observations. *Frontiers in Ecology and the Environment*, *10*(4), 195–201.

Masad, D., & Kazil, J. (2015). Mesa: An agent-based modeling framework. *14th PYTHON in Science Conference*, *2015*, 53–60.

Mathioulakis, S., & Photis, Y. N. (2017). Using the sleuth model to simulate future urban growth in the greater eastern attica area, greece. *European Journal of Geography*, *8*(2).

McCafferty, D. J., Gallon, S., & Nord, A. (2015). Challenges of measuring body temperatures of free-ranging birds and mammals. *Animal Biotelemetry*, *3*(1), 1–10.

McCarthy, E. D., Martin, J. M., Boer, M. M., & Welbergen, J. A. (2021). Drone-based thermal remote sensing provides an effective new tool for monitoring the abundance of roosting fruit bats. *Remote Sensing in Ecology and Conservation*, *7*(3), 461–474.

McKenzie, G., Romm, D., Zhang, H., & Brunila, M. (2022). Privyto: A privacy-preserving location-sharing platform. *Transactions in GIS*, *26*(4), 1703–1717.

McLane, A. J., Semeniuk, C., McDermid, G. J., Tomback, D. F., Lorenz, T., & Marceau, D. (2017). Energetic behavioural-strategy prioritization of clark's nutcrackers in whitebark pine communities: An agent-based modeling approach. *Ecological Modelling*, *354*, 123–139.

Michelot, T., Langrock, R., & Patterson, T. A. (2016). Movehmm: An r package for the statistical modelling of animal movement data using hidden markov models. *Methods in Ecology and Evolution*, *7*(11), 1308–1315.

Miller, H. J., Dodge, S., Miller, J., & Bohrer, G. (2019). Towards an integrated science of movement: Converging research on animal movement ecology and human mobility science. *International Journal of Geographical Information Science*, *33*(5), 855–876.

Mohibullah, W., & Julie, S. J. (2013). Developing an agent model of a missing person in the wilderness. *2013 IEEE international conference on systems, man, and cybernetics*, 4462–4469.

Mordvintsev, A., Krzhizhanovskaya, V., Lees, M., & Sloot, P. (2014). Simulation of city evacuation coupled to flood dynamics. *Pedestrian and Evacuation Dynamics 2012*, 485–499.

Musiani, M., Anwar, S. M., McDermid, G. J., Hebblewhite, M., & Marceau, D. J. (2010). How humans shape wolf behavior in banff and kootenay national parks, canada. *Ecological Modelling*, *221*(19), 2374–2387.

Nan, X., Iles, I. A., Yang, B., & Ma, Z. (2022). Public health messaging during the covid-19 pandemic and beyond: Lessons from communication science. *Health communication*, *37*(1), 1–19.

Nara, A., & Torrens, P. M. (2005). Inner-city gentrification simulation using hybrid models of cellular automata and multi-agent systems. *Proceedings of the Geocomputation 2005 conference. University of Michigan, Michigan.*

Nasir, M., Lim, C. P., Nahavandi, S., & Creighton, D. (2014). Prediction of pedestrians routes within a built environment in normal conditions. *Expert Systems with Applications*, *41*(10), 4975–4988.

Nathan, R., Getz, W. M., Revilla, E., Holyoak, M., Kadmon, R., Saltz, D., & Smouse, P. E. (2008). A movement ecology paradigm for unifying organismal movement research. *Proceedings of the National Academy of Sciences*, *105*(49), 19052–19059.

Neeganagwedgin, E. (2019). Indigenous lands and territories: Self-determination, activism and canada's white paper. *Whitehead J. Dipl. & Int'l Rel.*, *21*, 84.

Neumann, W., Martinuzzi, S., Estes, A. B., Pidgeon, A. M., Dettki, H., Ericsson, G., & Radeloff, V. C. (2015). Opportunities for the application of advanced remotely-sensed data in ecological studies of terrestrial animal movement. *Movement ecology*, *3*, 1–13.

Nigussie, T. A., & Altunkaynak, A. (2017). Modeling urbanization of istanbul under different scenarios using sleuth urban growth model. *Journal of Urban Planning and Development*, *143*(2), 04016037.

Nunn, C. L., Thrall, P. H., Leendertz, F. H., & Boesch, C. (2011). The spread of fecally transmitted parasites in socially-structured populations. *PloS one*, *6*(6), e21677.

Oishi, Y., Oguma, H., Tamura, A., Nakamura, R., & Matsunaga, T. (2018). Animal detection using thermal images and its required observation conditions. *Remote Sensing*, *10*(7), 1050.

Oloo, F., & Wallentin, G. (2017). An adaptive agent-based model of homing pigeons: A genetic algorithm approach. *ISPRS International Journal of Geo-Information*, *6*(1), 27.

Onsted, J. A., & Clarke, K. C. (2011). Forecasting enrollment in differential assessment programs using cellular automata. *Environment and planning B: Planning and design*, *38*(5), 829–849.

Orellana, D., Bregt, A. K., Ligtenberg, A., & Wachowicz, M. (2012). Exploring visitor movement patterns in natural recreational areas. *Tourism Management*, *33*(3), 672–682.

O'Sullivan, D., Evans, T., Manson, S., Metcalf, S., Ligmann-Zielinska, A., & Bone, C. (2016). Strategic directions for agent-based modeling: Avoiding the yaawn syndrome. *Journal of land use science*, *11*(2), 177–187.

Page, S. E. (2008). Uncertainty, difficulty, and complexity. *Journal of Theoretical Politics*, *20*(2), 115–149. https://doi.org/10.1177/0951629807085815

Pasternak, S., & King, H. (2019). Land back. *A Yellowhead Institute Red Paper*.

Patel, A., Crooks, A., & Koizumi, N. (2012). Slumulation: An agent-based modeling approach to slum formations. *Journal of Artificial Societies and Social Simulation*, *15*(4), 2.

Patterson, T. A., Basson, M., Bravington, M. V., & Gunn, J. S. (2009). Classifying movement behaviour in relation to environmental conditions using hidden markov models. *Journal of Animal Ecology*, *78*(6), 1113–1123.

Payne, N. L., Taylor, M. D., Watanabe, Y. Y., & Semmens, J. M. (2014). From physiology to physics: Are we recognizing the flexibility of biologging tools? *Journal of Experimental Biology*, *217*(3), 317–322.

Pellegrini, A., Di Sanzo, P., Bevilacqua, B., Duca, G., Pascarella, D., Palumbo, R., Ramos, J. J., Piera, M. A., & Gigante, G. (2020). Simulation-based evolutionary optimization of air traffic management. *IEEE access*, *8*, 161551–161570.

Perez, L., & Dragicevic, S. (2009). An agent-based approach for modeling dynamics of contagious disease spread. *International journal of health geographics*, *8*(1), 1–17.

Perez, L., & Dragicevic, S. (2012). Landscape-level simulation of forest insect disturbance: Coupling swarm intelligent agents with gis-based cellular automata model. *Ecological modelling*, *231*, 53–64.

Perez, L., Eun-kyeong, K., & Sengupta, R. (2018). Agent-based models and complexity science in the age of geospatial big data. *Cham: Springer Nature. doi*, *10*, 978–3.

Pérez, L., & Dragićević, S. (2011). Forestsimmpb: A swarming intelligence and agent-based modeling approach for mountain pine beetle outbreaks. *Ecological informatics*, *6*(1), 62–72.

Pirotta, E., New, L., Harwood, J., & Lusseau, D. (2014). Activities, motivations and disturbance: An agent-based model of bottlenose dolphin behavioral dynamics and interactions with tourism in doubtful sound, new zealand. *Ecological Modelling*, *282*, 44–58.

Poe, M. R., Norman, K. C., & Levin, P. S. (2014). Cultural dimensions of socioecological systems: Key connections and guiding principles for conservation in coastal environments. *Conservation Letters*, *7*(3), 166–175.

Purves, R. S., Laube, P., Buchin, M., & Speckmann, B. (2014). Moving beyond the point: An agenda for research in movement analysis with real data.

Radakov, D. V. (1973). Schooling in the ecology of fish. *(*

Rakowski, F., Gruziel, M., Bieniasz-Krzywiec, Ł., & Radomski, J. P. (2010). Influenza epidemic spread simulation for poland—a large scale, individual based model study. *Physica A: Statistical Mechanics and its Applications*, *389*(16), 3149–3165.

Ramanath, A. M., & Gilbert, N. (2004). The design of participatory agent-based social simulations. *Journal of Artificial Societies and Social Simulation*, *7*(4).

Ravenstein, E. G. (1885). The laws of migration.

Rayfield, B., Pelletier, D., Dumitru, M., Cardille, J. A., & Gonzalez, A. (2016). Multipurpose habitat networks for short-range and long-range connectivity: A new method combining graph and circuit connectivity. *Methods in Ecology and Evolution*, *7*(2), 222–231.

Reilly, A. C., Guikema, S. D., Zhu, L., & Igusa, T. (2017). Evolution of vulnerability of communities facing repeated hazards. *PLoS One*, *12*(9), e0182719.

Ren, C., Yang, C., & Jin, S. (2009). Agent-based modeling and simulation on emergency evacuation. *Complex Sciences: First International Conference, Complex 2009, Shanghai, China, February 23-25, 2009, Revised Papers, Part 2 1*, 1451–1461.

Rienow, A., & Goetzke, R. (2015). Supporting sleuth–enhancing a cellular automaton with support vector machines for urban growth modeling. *Computers, Environment and Urban Systems*, *49*, 66–81.

Rienow, A., & Stenger, D. (2014). Geosimulation of urban growth and demographic decline in the ruhr: A case study for 2025 using the artificial intelligence of cells and agents. *Journal of geographical systems*, *16*, 311–342.

Rietz, J., van Beeck Calkoen, S. T., Ferry, N., Schlüter, J., Wehner, H., Schindlatz, K.-H., Lackner, T., von Hoermann, C., Conraths, F. J., Müller, J., et al. (2023). Drone-based thermal imaging in the detection of wildlife carcasses and disease management. *Transboundary and Emerging Diseases*, *2023*.

Robinson, M. C. (1992). Rivers in miniature: The mississippi basin model. *Builders and fighters: US Army Engineers in World War II. Fort Belvoir, VA: Office of History, United States Army Corps of Engineers*.

Roncoli, C., Ingram, K., & Kirshen, P. (2002). Reading the rains: Local knowledge and rainfall forecasting in burkina faso. *Society & Natural Resources*, *15*(5), 409–427.

Rosés, R., Kadar, C., Gerritsen, C., & Rouly, C. (2018). Agent-based simulation of offender mobility: Integrating activity nodes from location-based social networks. *Aamas*, 804–812.

Roy, D., Lees, M. H., Palavalli, B., Pfeffer, K., & Sloot, M. P. (2014). The emergence of slums: A contemporary view on simulation models. *Environmental Modelling & Software*, *59*, 76–90.

Russo, L., Russo, P., Vakalisc, D., & Siettos, C. (2014). Detecting weak points of wildland fire spread: A cellular automata model risk assessment simulation approach. *Chem. Eng.-New York*, *36*, 253–258.

Rybarczyk, G. (2010). *Bicycle travel demand forecasting using geographic information systems and agent based modeling*. The University of Wisconsin-Milwaukee.

Sabri, S., M. Ludin, A. N. M., & Ho, C. S. (2012). Conceptual design for an integrated geosimulation and analytic network process (anp) in gentrification appraisal. *Applied Spatial Analysis and Policy*, *5*, 253–271.

Sabri, S., & Yaakup, A. (2008). Exploring urban modeling methodologies to better figure out urban gentrification dynamics in developing countries. *Jurnal Alam Bina*, (2).

Schlingmann, A., Graham, S., Benyei, P., Corbera, E., Sanesteban, I. M., Marelle, A., Soleymani-Fard, R., & Reyes-Garcı´a, V. (2021). Global patterns of adaptation to climate change by indigenous peoples and local communities. a systematic review. *Current opinion in environmental sustainability*, *51*, 55–64.

Schlüter, M., Haider, L. J., Lade, S. J., Lindkvist, E., Martin, R., Orach, K., Wijermans, N., & Folke, C. (2019). Capturing emergent phenomena in social-ecological systems. *Ecology and Society*, *24*(3).

Sejian, V., Shashank, C. G., Silpa, M. V., Madhusoodan, A. P., Devaraj, C., & Koenig, S. (2022). Non-invasive methods of quantifying heat stress response in farm animals with special reference to dairy cattle. *Atmosphere*, *13*(10), 1642.

Semeniuk, C. A., Haider, W., Cooper, A., & Rothley, K. D. (2010). A linked model of animal ecology and human behavior for the management of wildlife tourism. *Ecological Modelling*, *221*(22), 2699–2713.

Sengupta, R., & Sieber, R. (2007). Geospatial agents, agents everywhere... *Transactions in GIS*, *11*(4), 483–506.

Sequeira, A. M., O'Toole, M., Keates, T. R., McDonnell, L. H., Braun, C. D., Hoenner, X., Jaine, F. R., Jonsen, I. D., Newman, P., Pye, J., et al. (2021). A standardisation framework for bio-logging data to advance ecological research and conservation. *Methods in Ecology and Evolution*, *12*(6), 996–1007.

Shekhar, S., Feiner, S., & Aref, W. G. (2015). From gps and virtual globes to spatial computing-2020. *GeoInformatica*, *19*, 799–832.

Shekhar, S., Jiang, Z., Ali, R. Y., Eftelioglu, E., Tang, X., Gunturi, V. M., & Zhou, X. (2015). Spatiotemporal data mining: A computational perspective. *ISPRS International Journal of Geo-Information*, *4*(4), 2306–2338.

Sieber, R. E., & Haklay, M. (2015). The epistemology (s) of volunteered geographic information: A critique. *Geo: Geography and Environment*, *2*(2), 122–136.

Smith, C. D. (2014). Modelling migration futures: Development and testing of the rainfalls agent-based migration model–tanzania. *Climate and Development*, *6*(1), 77–91.

Snively, G., & Corsiglia, J. (2001). Discovering indigenous science: Implications for science education. *Science education*, *85*(1), 6–34.

Song, Y., Gong, J., Li, Y., Cui, T., Fang, L., & Cao, W. (2013). Crowd evacuation simulation for bioterrorism in micro-spatial environments based on virtual geographic environments. *Safety science*, *53*, 105–113.

Spielman, S., & Harrison, P. (2014). The c o-evolution of residential segregation and the built environment at the turn of the 20th century: As chelling model. *Transactions in GIS*, *18*(1), 25–45.

Strandburg-Peshkin, A., Farine, D. R., Couzin, I. D., & Crofoot, M. C. (2015). Shared decision-making drives collective movement in wild baboons. *Science*, *348*(6241), 1358–1361.

Su, R., Dodge, S., & Goulias, K. G. (2022). Understanding the impact of temporal scale on human movement analytics. *Journal of Geographical Systems*, *24*(3), 353–388.

Suleimenova, D., Bell, D., & Groen, D. (2017). A generalized simulation development approach for predicting refugee destinations. *Scientific reports*, *7*(1), 13377.

Sumpter, D., Buhl, J., Biro, D., & Couzin, I. (2008). Information transfer in moving animal groups. *Theory in biosciences*, *127*, 177–186.

Sun, S., & Manson, S. M. (2015). Simple agents, complex emergent city: Agent-based modeling of intraurban migration. *Computational approaches for urban environments*, 123–147.

Sutton, R. S., & Barto, A. G. (1999). Reinforcement learning: An introduction. *Robotica*, *17*(2), 229–235.

Takabatake, T., Shibayama, T., Esteban, M., Ishii, H., & Hamano, G. (2017). Simulated tsunami evacuation behavior of local residents and visitors in kamakura, japan. *International journal of disaster risk reduction*, *23*, 1–14.

Tan, L., Hu, M., & Lin, H. (2015). Agent-based simulation of building evacuation: Combining human behavior with predictable spatial accessibility in a fire emergency. *Information Sciences*, *295*, 53–66.

Tang, W., & Bennett, D. A. (2010). Agent-based modeling of animal movement: A review. *Geography Compass*, *4*(7), 682–700.

Thurfjell, H., Ciuti, S., & Boyce, M. S. (2014). Applications of step-selection functions in ecology and conservation. *Movement ecology*, *2*, 1–12.

Tirivangasi, H. M., & Nyahunda, L. (2019). Challenges faced by rural people in mitigating the effects of climate change in the mazungunye communal lands, zimbabwe. *Jàmbá: Journal of Disaster Risk Studies*, *11*(1), 1–9.

Torrens, P. M. (2010). Agent-based models and the spatial sciences. *Geography Compass*, *4*(5), 428–448.

Torrens, P. M. (2012). Moving agent pedestrians through space and time. *Annals of the Association of American Geographers*, *102*(1), 35–66.

Torrens, P. M. (2014). High-resolution space–time processes for agents at the built–human interface of urban earthquakes. *International Journal of Geographical Information Science*, *28*(5), 964–986.

Torrens, P. M., & Nara, A. (2007). Modeling gentrification dynamics: A hybrid approach. *Computers, environment and urban systems*, *31*(3), 337–361.

Tyler, N. J., Turi, J. M., Sundset, M. A., Bull, K. S., Sara, M. N., Reinert, E., Oskal, N., Nellemann, C., McCarthy, J., Mathiesen, S., et al. (2007). Saami reindeer pastoralism under climate change: Applying a generalized framework for vulnerability studies to a sub-arctic social–ecological system. *Global Environmental Change*, *17*(2), 191–206.

Ullman, E., Boyce, R., & Harris, C. (1980). Geography as spatial interaction. *University of Washington Press*.

Unruh, W. (1981). Experimental black-hole evaporation? *Physical Review Letters*, *46*(21), 1351.

Unruh, W. (2016). Experimental black hole evaporation.

Veraverbeke, S., Dennison, P., Gitas, I., Hulley, G., Kalashnikova, O., Katagis, T., Kuai, L., Meng, R., Roberts, D., & Stavros, N. (2018). Hyperspectral remote sensing of fire: State-of-the-art and future perspectives. *Remote Sensing of Environment*, *216*, 105–121.

Wagner, N., & Agrawal, V. (2014). An agent-based simulation system for concert venue crowd evacuation modeling in the presence of a fire disaster. *Expert Systems with Applications*, *41*(6), 2807–2815.

Wang, H., Mostafizi, A., Cramer, L. A., Cox, D., & Park, H. (2016). An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. *Transportation Research Part C: Emerging Technologies*, *64*, 86–100.

Whoriskey, K., Auger-Méthé, M., Albertsen, C. M., Whoriskey, F. G., Binder, T. R., Krueger, C. C., & Mills Flemming, J. (2017). A hidden markov movement model for rapidly identifying behavioral states from animal tracks. *Ecology and evolution*, *7*(7), 2112–2121.

Widener, M. J., Horner, M. W., & Ma, K. (2015). Positioning disaster relief teams given dynamic service demand: A hybrid agent-based and spatial optimization approach. *Transactions in GIS*, *19*(2), 279–295.

Widener, M. J., Horner, M. W., & Metcalf, S. S. (2012). Simulating the effects of social networks on people's hurricane evacuation rates.

Wikelski, M., Kays, R. W., Kasdin, N. J., Thorup, K., Smith, J. A., & Swenson Jr, G. W. (2007). Going wild: What a global small-animal tracking system could do for experimental biologists. *Journal of Experimental Biology*, *210*(2), 181–186.

Willcock, S., Cooper, G. S., Addy, J., & Dearing, J. A. (2023). Earlier collapse of anthropocene ecosystems driven by multiple faster and noisier drivers. *Nature Sustainability*, 1–12.

Willem, L., Verelst, F., Bilcke, J., Hens, N., & Beutels, P. (2017). Lessons from a decade of individual-based models for infectious disease transmission: A systematic review (2006-2015). *BMC infectious diseases*, *17*, 1–16.

Williams, H. J., Taylor, L. A., Benhamou, S., Bijleveld, A. I., Clay, T. A., de Grissac, S., Demšar, U., English, H. M., Franconi, N., Gómez-Laich, A., et al. (2020). Optimizing the use of biologgers for movement ecology research. *Journal of Animal Ecology*, *89*(1), 186–206.

Wilmers, C. C., Nickel, B., Bryce, C. M., Smith, J. A., Wheat, R. E., & Yovovich, V. (2015). The golden age of bio-logging: How animal-borne sensors are advancing the frontiers of ecology. *Ecology*, *96*(7), 1741–1753.

Wilson, S., Davies, T. E., Hazarika, N., & Zimmermann, A. (2015). Understanding spatial and temporal patterns of human–elephant conflict in assam, india. *Oryx*, *49*(1), 140–149.

Winkler, D. W., Jørgensen, C., Both, C., Houston, A. I., McNamara, J. M., Levey, D. J., Partecke, J., Fudickar, A., Kacelnik, A., Roshier, D., et al. (2014). Cues, strategies, and outcomes: How migrating vertebrates track environmental change. *Movement Ecology*, *2*, 1–15.

Wintle, B. A., Elith, J., & Potts, J. M. (2005). Fauna habitat modelling and mapping: A review and case study in the lower hunter central coast region of nsw. *Austral Ecology*, *30*(7), 719–738.

Wu, X., Hu, Y., He, H., Xi, F., & Bu, R. (2010). Study on forecast scenarios for simulation of future urban growth in shenyang city based on sleuth model. *Geo-spatial Information Science*, *13*(1), 32–39.

Xu, F., Li, Y., Jin, D., Lu, J., & Song, C. (2021). Emergence of urban growth patterns from human mobility behavior. *Nature Computational Science*, *1*(12), 791–800.

Yabe, T., Rao, P. S. C., Ukkusuri, S. V., & Cutter, S. L. (2022). Toward data-driven, dynamical complex systems approaches to disaster resilience. *Proceedings of the National Academy of Sciences*, *119*(8), e2111997119.

Yang, Y., Atkinson, P. M., & Ettema, D. (2011). Analysis of cdc social control measures using an agent-based simulation of an influenza epidemic in a city. *BMC infectious diseases*, *11*(1), 1–10.

Yin, L. (2009). The dynamics of residential segregation in buffalo: An agent-based simulation. *Urban Studies*, *46*(13), 2749–2770.

Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for travel demand simulation for hurricane evacuation. *Transportation research part C: emerging technologies*, *42*, 44–59.

Young, D. A. (2002). A new space-time computer simulation method for human migration. *American anthropologist*, *104*(1), 138–158.

Yu, H., Kong, B., Wang, Q., Liu, X., & Liu, X. (2020). Hyperspectral remote sensing applications in soil: A review. *Hyperspectral Remote Sensing*, 269–291.

Zein, B., Long, J., Safi, K., Kölzsch, A., Benitez-Paez, F., Wikelski, M., Kruckenberg, H., & Demšar, U. (2022). Simulating geomagnetic bird navigation using novel high-resolution geomagnetic data. *Ecological Informatics*, *69*, 101689.

Zheng, X., Zhong, T., & Liu, M. (2009). Modeling crowd evacuation of a building based on seven methodological approaches. *Building and environment*, *44*(3), 437–445.

Zhou, L., Dang, X., Sun, Q., & Wang, S. (2020). Multi-scenario simulation of urban land change in shanghai by random forest and ca-markov model. *Sustainable Cities and Society*, *55*, 102045.

Zipf, G. K. (1940). The generalized harmonic series as a fundamental principle of social organization. *The Psychological Record*, *4*, 41.

Zook, M., Kraak, M.-J., & Ahas, R. (2015). Geographies of mobility: Applications of location-based data.

Zou, Y., Torrens, P. M., Ghanem, R. G., & Kevrekidis, I. G. (2012). Accelerating agent-based computation of complex urban systems. *International Journal of Geographical Information Science*, *26*(10), 1917–1937.